Optimisation of hedging-integrated rule curves for reservoir operation

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ABSTRACT

Reservoir managers use operational rule curves as guides for managing and operating reservoir systems. However, this approach saves no water for impending droughts, resulting in large shortages during such droughts. This problem can be tempered by integrating hedging with the rule curves to curtail the water releases during normal periods of operation and use the saved water to limit the amount and impact of water shortages during droughts. However, determining the timing and amount of hedging is a challenge.

This thesis presents the application of genetic algorithms (GA) for the optimisation of hedging-integrated reservoir rule curves. However, due to the challenge of establishing the boundary of feasible region in standard GA (SGA), a new development of the GA i.e. the dynamic GA (DGA), is proposed. Both the new development and its hedging policies were tested through extensive simulations of the Ubonratana reservoir (Thailand). The first observation was that the new DGA was faster and more efficient than the SGA in arriving at an optimal solution. Additionally, the derived hedging policies produced significant changes in reservoir performance when compared to no-hedging policies. The performance indices analysed were reliability (time and volume), resilience, vulnerability and sustainability; the results showed that the vulnerability (i.e. average single periods shortage) in particular was significantly reduced with the optimised hedging rules as compared to using the no-hedging rule curves.

This study also developed a monthly inflow forecasting model using artificial neural networks (ANN) to aid reservoir operational decision-making. Extensive testing of the model showed that it was able to provide inflow forecasts with reasonable accuracy. The simulated effect on reservoir performance of forecasted inflows vis-à-vis other assumed reservoir inflow knowledge situations showed that the ANN forecasts were superior, further reinforcing the importance of good inflow information for reservoir operation.

The ability of hedging to harness the inherent buffering capacity of existing water resources systems for tempering water shortage (or vulnerability) without the need for expensive new-builds is a major outcome of this study. Although applied to Ubonratana, the study has utility for other regions of the world, where e.g. climate and other environmental changes are stressing the water availability situation.

DEDICATION

To my mother, Pongpen Abramson, who is waiting for me to go back home in Thailand.

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ABGA	Adaptive Boundary Genetic Glgorithm
ACF	Auto Correlation Function
ACO	Ant Colony Optimisation
ANN	Artificial Neural Networks
AR	Autoregressive
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
Avg	Average
BP	Back Propagation
CCF	Cross Correlation Function
CRC	Critical Rule Curve
DGA	Dynamic Genetic Algorithm
DP	Dynamic Programming
EGAT	Electricity Generating Authority of Thailand
eLRC	Existing Lower Rule Curve
ESR	Early Stopping Rule
eURC	Existing Upper Rule Curve
FCRC	Flood Control Rule Curve
FFMLP	Feed-Forward Multilayer Perceptron
FFNN	Feed-Forward Neural Networks
GA	Genetic Algorithm
GIS	Geographic Information System
HBMO	Honey-Bee Mating Optimisation
HEC	Hydrologic Engineering Centre
HEC-RAS	Hydraulic Engineering Center-River Analysis System
km^2	square kilometre
LM	Levenberg-Marquardt algorithm
LM-BP	Levenberg–Marquardt Back Propagation
LP	Linear Programming
LRC	Lower Rule Curve
MA	Moving Average
Max	Maximum
mm	Millimeter

Mm^3	million cubic meters
Min	minimum
Min.WL	minimum water level
MLBP	Multi-Layer Back Propagation
MLP	Multi-Layer Perceptron
MLFFN	Multi-Layer Feed-Forward Artificial Neuron Network
MSE	Mean Square Error
MSI	Modified Shortage Index
NHWL	Normal High Water Level
NLP	Nonlinear Programming
NSE or NASH	Nash-Sutcliffe efficiency
PACF	Partial autocorrelation function
PSO	Particle Swarm Optimisation
R	Regression
RID	Royal Irrigation Department
RMES	Root Mean Square Error
RNN	Recurrent Neural Network
STD	Standard Deviation
SGA	Standard Genetic Algorithm
SI	Sustainability Index
SS	Sum Squares of the period shortages
SSRT	Search Space Reduction Technique
SOP	Standard Operating Policy
sum	Summation
URC	Upper Rule Curve
USACE	United States Army Corps of Engineers
WA	Water Available
WEAP	Water Evaluation and Planning
WL	Water Level

LIST OF SYMBOLS

A_v	Surface area of reservoir in interval t
Cv	Coefficient of variation of annual runoff
D_t	Water demand during interval t
$D_{p,t}$	Public demand during interval t
$D_{d,t}$	Downstream or in-stream demand during interval t
$D_{i,t}$	Irrigation demand during interval t
D'_t	Actual water release during interval t
$D'_{p,t}$	Actual public release during interval t
$D'_{d,t}$	Actual downstream or in-stream release during interval t
$D'_{i,t}$	Actual irrigation release during interval t
e_t	Net evaporation in the interval t (mm)
φ	Resilience
f_s	Number of continuous sequences of failure periods
f_d	Total duration of the failures
g	Generations in genetic algorithm
Ka	Active storage capacity
$\mathrm{LB_i}$	Value of the parameter x_i, for the lower limit of initial constraint boundary in dynamic algorithm
m	Hurst's standardized net inflow parameter
max(shk)	Maximum shortfall during each continuous failure sequence
N	Total number of time periods
N_s	Total number of time periods during which the demand was met
η'	Vulnerability (volumetric unit)
η	Dimensionless vulnerability metric
O_t	Volume of outflow during interval t
Q_t	Inflow to the storage during interval t
R	Correlation coefficient
R_t	Time-based reliability
R_v	Volume-based reliability
r	Repetition in genetic algorithm
λ	Sustainability index
λ_G	Sustainability index of users group
S_t	Volume of storage at the beginning of interval t

S_{t+1}	Volume of storage at the end of interval t
TS_t	Total shortage during interval t
UB_i	Value of the parameter x_i, for the upper limit of initial constraint boundary in dynamic algorithm
$\mathrm{Xb}_{\mathrm{i,k}}$	Value of the parameter x_{i} for the best performing individual of the current group k in dynamic genetic algorithm
$xb_{i,g}$	Value of parameter for the best performing individual in generation g
$x\ max_i$	Value of the parameter x_i, for the upper bounds of the initial limit in genetic algorithm
$\mathrm{xmax}_{\mathrm{i,(g+1)}}$	Value of the parameter x_i, for the upper bounds of the new limit in genetic algorithm
$xmean_{i,g}$	Mean value of the whole population for the parameter x_i, in current generation
$x\ min_i$	Value of the parameter x_i, for the lower bounds of the initial limit in genetic algorithm
$\mathrm{xmin}_{\mathrm{i,(g+1)}}$	Value of the parameter x_i, for the lower bounds of the new limit in genetic algorithm
Y_t	Spilling during during interval t
y_{sim}	Predicted output
y_{obs}	Observed output or target

LIST OF PUBLICATIONS

Publications

1. Chiamsathit, C.,Adeloye, A.J. and Soundharajan, B.S. (2014) Assessing competing policies at Ubonratana reservoir, Thailand - Proceedings of the Institution of Civil Engineers - Water Management 2014. 167(10). p.551-560 (see Appendix C1).

2. Chiamsathit, C., Adeloye, A. J. and Soundharajan, B.S. (2014) Genetic algorithms optimization of hedging rules for operation of the multi-purpose Ubonratana reservoir in Thailand. *Proc. IAHS*. 364. p.507-512. DOI: 10.5194/piahs-364-507-2014. (see Appendix C2).

3. Chiamsathit, C., Adeloye, A.J. and Soundharajan, B.S. (2015) A new dynamic genetic algorithm for optimizing reservoir operating rule curves: a case study of the Ubonratana reservoir, Thailand, the IWRA World Water Congress XV, Edinburgh, 25-29 May 2015 (see Appendix C3).

4. Chiamsathit, C., Adeloye, A.J. and Soundharajan, B.S. (2016) Inflow forecasting using Artificial Neural Networks for reservoir operation. In Bochum IASH 7th international water resources management conference of ICWRS, 18-20 May 2016. *Proc. IAHS*. 93. p.1–6. DOI: 10.5194/piahs-364-507-2014 (Accepted) (see Appendix C4).

Oral Presentations

1. Chiamsathit, C. (2014) Genetic algorithms optimization of hedging rules for operation of the multi-purpose Ubonratana reservoir in Thailand. in IAHS-AISH Proceedings and Reports. vol. 364, IAHS Press, pp. 507-512, Bologna IAHS 2014 - 6th IAHS-EGU International Symposium on Integrated Water Resources Management, Bologna, 4-6 June 2014.

2. Chiamsathit, C. (2015) A new dynamic genetic algorithm for optimizing reservoir operating rule curves: a case study of the Ubonratana reservoir, Thailand, the IWRA World Water Congress XV, Edinburgh, UK, 25-29 May 2015

3. Chiamsathit, C. (2015) The effect of establishing boundary on Genetic algorithm (GA) for optimising reservoir operating rule curves. The 26th IUGG General Assembly of the International Union of Geodesy and Geophysics, Prague, the Czech Republic, June 22 - July 2, 2015.

Poster Presentations

1. Chiamsathit, C. (2013) Simulation-Optimisation of Ubonratana reservoir operational control in northeastern Thailand. Poster presentation in Infrastructure & Environment Scotland 1st Postgraduate Conference, 3 June 2013, Heriot-University, Edinburgh (see Appendix D1)

2. Chiamsathit, C. (2014) Simulation-Optimisation of Ubonratana reservoir hedging rules in northeastern Thailand. Poster presentation in the inauguration of the water and drainage lab, 7 May 2014 Heriot-University, Edinburgh (see Appendix D2)

3. Chiamsathit, C. (2014) Simulation-Optimisation of Ubonratana reservoir hedging rules in northeastern Thailand. Poster presentation in Infrastructure & Environment Scotland 2nd Postgraduate Conference, 27 August 2014, Heriot-University, Edinburgh (see Appendix D3)

4. Chiamsathit, C. (2015) Simulation-Optimisation of Ubonratana reservoir hedging rules in northeastern Thailand. Poster presentation in National Women in Engineering Day, 23 June 2015, Heriot-University, Edinburgh (see Appendix D3)

Chapter 1 Introduction

1.1 Background

Water storage reservoirs play a key role in managing the water resources of local and regional water supply systems. Due to temporal and spatial variation of streamflow and rainfall, natural streamflow either be inadequate for water supply, irrigation, and hydropower generation purposes or too much that it causes flooding and damages to surrounding regions. A reservoir is required to retain excess water during high streamflow periods and heavy rains and release the water gradually, based on water demand during low flow or non-rainy periods. The storage of the floodwater will reduce the impact of floods during heavy rain while its release during non-rainy periods will help to combat droughts in regions served by the reservoir. Moreover, reservoirs often have multiple functions such as to generate electricity and for enhancing downstream flow thereby maintaining a healthy ecosystem.

Historical streamflow time series and expected water demand are required for sizing of reservoir capacity. Although the historical streamflow time series may be long and thus contain a significant critical period on which to base the timing, there is no guarantee that this historical series will be repeated exactly during future operations of the reservoir. This is because of changes in land use, climate, rainfall, monsoon periods, demand for water and the variability introduced by the stochasticity of these factors and inputs. For example, urbanisation and industrialisation can lead to increased water demand and changes in the climate (Bronstert, 2003). This in turn can affect the large scale hydrological cycle, causing increases in the humidity content in the atmosphere and changing precipitation forms (Bates et al., 2008). There is, therefore, the need to properly operate the reservoir and to constantly review operational policy performance and, where necessary, to devise improvements.

Reservoir operation is concerned with allocating the available water in a reservoir in a way that maximises the overall performance and benefits of the reservoir. The derivation of reservoir operating policies has engaged water resources researchers for a long time; analyses have involved the use of various optimisation schemes, and water scarcity related objective functions (see Hashimoto et al., 1982; ReVelle et al., 1969; Yazicigil et al., 1983; Shiau and Lee, 2005; Shih and ReVelle, 1995; Yeh, 1985). For example, Yazicigil et al. (1983) applied a linear programming optimisation model for daily real-time operation of a multi-reservoir system by using forecasts of precipitation, inflow, and tributary flow. A number of flow zones and reservoir elevation zones are assumed. The objective is to minimise the total penalties on the deviations from both the target storage and the target release levels aggregated over the four reservoirs in the Green River Basin in Kentucky, USA. The study showed that the penalty could be reduced by 45.8% compared to historical operations. Although, the linear programing optimisation guaranteed reaching the optimum solution, the fact that all equations - objective function and constraint equations - must be linear limits its applicability. In reality, most objective functions are nonlinear in practical cases in water resources management. Yeh (1985) conducted a review of optimisation approaches and concluded that although the literature identified certain improvements in optimisation approaches, a practical method for reservoir analysis had not been achieved at that time. Rogers and Fiering (1986) outlined reasons why water management practitioners were reluctant to apply mathematical optimization algorithms as proposed by researchers. These included deficiencies in databases, modelling inadequacies, institutional resistance to change, and the fundamental insensitivity of many actual systems to wide variations in design choices. This was in part because operators were excluded from the policy-making process and partly because simplified computer programmes and operation policies were not suitable for complicated, actual cases.

During planning analysis of reservoirs when there are no pre-determined operating policies, heuristic operating policies are often utilised. For the planning of single reservoir systems for example, a commonly used heuristic operating policy is the standard operating policy (SOP) (McMahon and Adeloye, 2005). The SOP illustrated in Figure 1.1 stipulates supplying the demand if sufficient water is available but if not, all the available water is supplied leaving the reservoir empty (Hashimoto et al., 1982). The SOP is very easy to use and can be shown to maximise the overall volumetric reliability of the reservoir system; however, because it does not attempt to redistribute water in a way that protects periods of extreme low flows, its vulnerability (or maximum single period water shortage) can be very high if the reservoir encounters an extremely dry period during its operation, as explained by Adeloye et al. (2001).

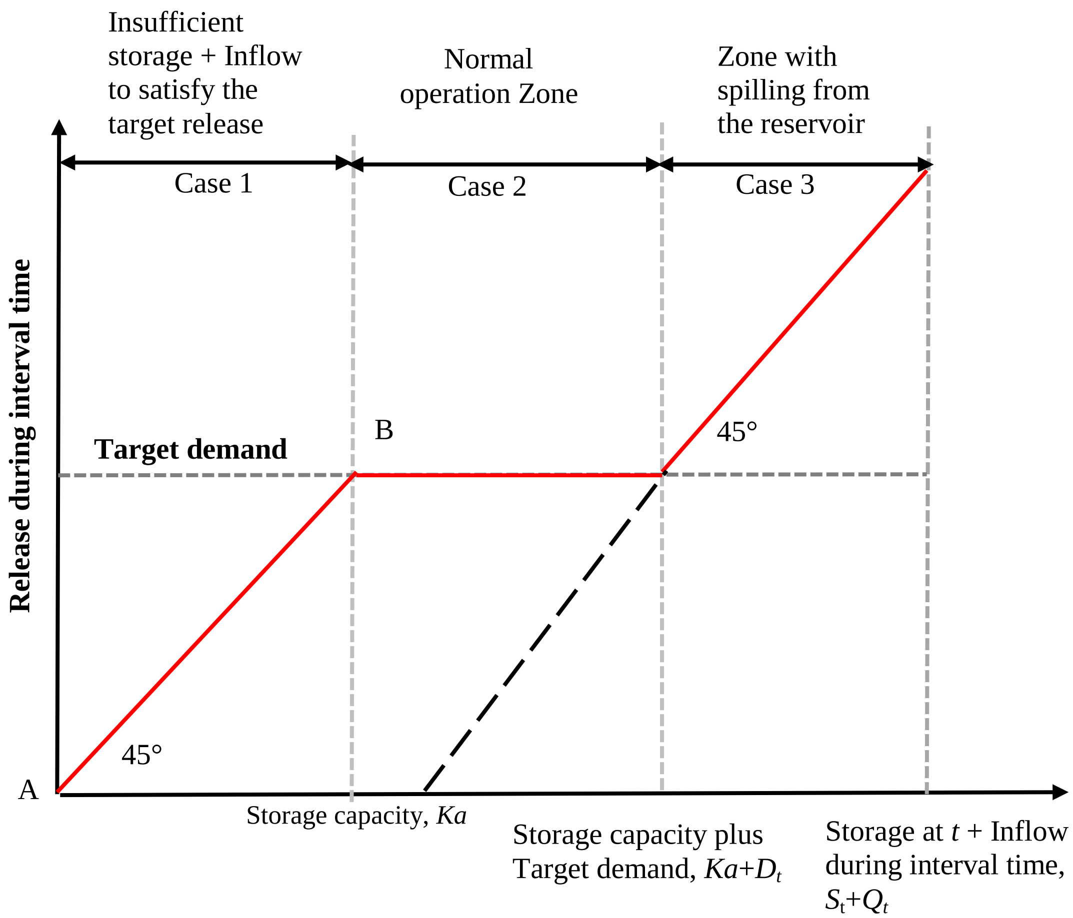


Figure 1.1 A standard operating policy (SOP) illustrated

The above, and other problems associated with formalised reservoir operating policies including the SOP, have led most reservoir operators to rely on the use of heuristic rule curves to guide reservoir operation. Rule curves (see Figure 1.2 for illustration) provide target levels that must be maintained in a reservoir at various periods in order to meet the demand over the drawdown–refill cycle of the reservoir. Unlike the operating policies, rule curves can be derived using simulation studies of the reservoir; specifically the modified sequent peak algorithm (see Adeloye et al., 2001; McMahon and Adeloye, 2005), which is immune from the misbehaviour of traditional behaviour analysis as reported by Pretto et al. (1997).

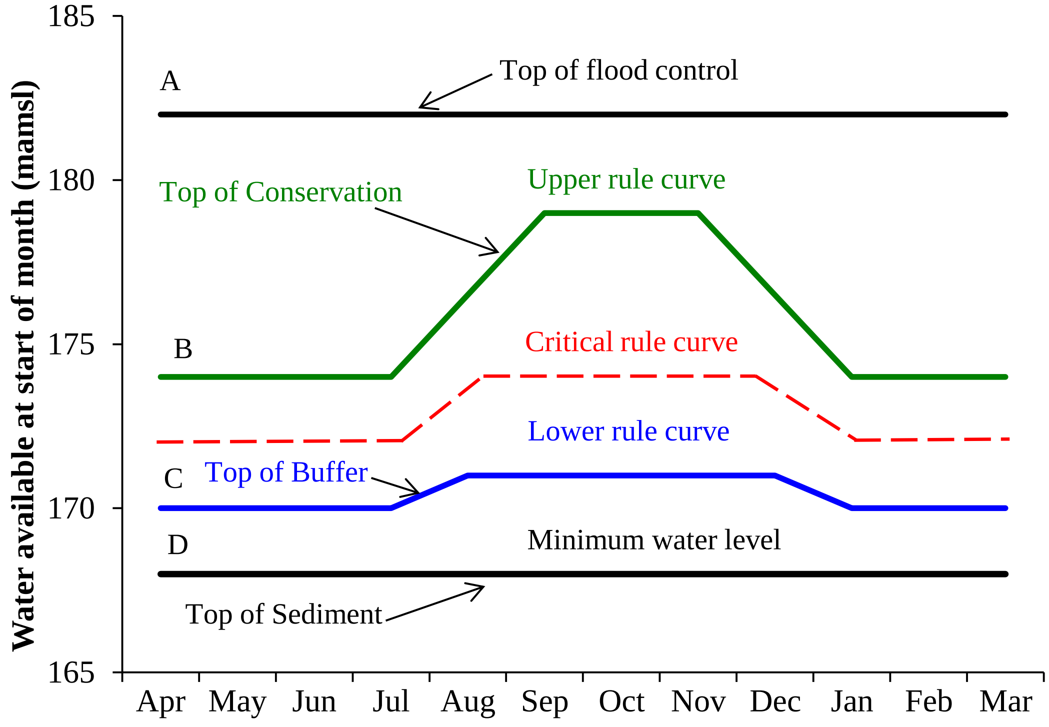


Figure 1.2 Schematic of rule curves for reservoir operation

Rule curves policy defines upper and lower rule curves, to guide the reservoir release to meet water requirements: as long as the available water at the start of a period is within the space bounded by the two curves, an attempt is made to meet the full demand during that period. The available water is the sum of the starting storage level and the expected inflow during the period. During the periods of drought, the available water will be low, i.e. close to the lower rule curve making the operator to embark on a forced cutback in order to remain within the bounds of the upper and lower rule curves for the start of the next operating period. The consequence of this is that the resulting shortage during such droughts can be very large. This problem can be tempered by deliberate water rationing during normal operational periods. A normal operational period has sufficient water to meet the full demand but during deliberate rationing rather than supply the full demands, the supply is curtailed and the saved water can be used to limit the amount and impact of any water shortages during droughts. The water rationing is called the hedging rule; the rationale for this is that it is better to have many small water shortages to which water users can readily adapt than fewer large, crippling shortages (Tu et al., 2003; 2008: Eum et al., 2011). For example, Fiering (1982) noted that modest water shortages (≤ 25% of demand) can be tolerated by most users; large shortages will be much more problematic.

Thus, both the SOP and traditional rule curves when used for reservoir operation produce large single period shortages or vulnerability. Consequently, several investigators (e.g. Srinivasan and Philipose, 1996) have researched ways of improving the performance of the SOP by attempting to develop a system of water hedging so that water can be held back during the period of relative wetness to meet some of the demands during the periods of extreme low flows. These efforts have resulted in single point or multiple points hedging policies associated with the SOP (Draper and Lund, 2004). The worrying aspect of some of these hedging policies integrated with the SOP is that they are recommending cutback in region A-B (see Figure 1.1) when the available water is insufficient. As noted by Adeloye et al. (2016), such a practice is inappropriate because it will end up intensifying the water shortage problem. For hedging to be effective, it must be implemented after point B in Figure 1.1, i.e. in the period of normal operation of the reservoir.

Integrating hedging with traditional rule curves involves developing a critical curve that lies between the upper and lower curves and that serves as the trigger for water cutback as illustrated in Figure 1.2. This zone-based approach to hedging ensures that the water rationing takes place during periods of normal operation of the reservoir, thus removing the limitation of a SOP-based hedging approach. The development of this critical curve and the determination of the associated hedging quantity have been attempted using various approaches. In general, simulation models can be used for developing operating policies; however, the process involves the repeated implementation of simulation models through the trial and error process (Kangrang and Hormwichian, 2008). Because the number of feasible solutions in even a moderately complex water resources system is quite large, the trial and error process in simulation is very time consuming. The Water Evaluation and Planning System (WEAP) is a popular software tool that uses such a simulation approach.

More recently, optimisation models have been used successfully to manage and operate complex reservoir systems, and to develop more efficient optimal policies. Various traditional optimisation methods e.g. linear and nonlinear programming (LP; NLP) and dynamic programing (DP) are widely used and are excellently described by Yeh (1985) and Wurbs (1993); they are also discussed in more detail in Chapter 2. The robustness of WEAP for example has been increased by the incorporation of linear programming solver, although, it is still not flexible enough for nonlinear problems. Recently, new optimisation schemes inspired by biology have been developed including genetic algorithms (GA), particle swarm optimisation (PSO), ant colony optimisation (ACO) and honey-bee mating optimisation (HBMO); these are also discussed further in Chapter 2. Of these evolutionary algorithms, however, GAs have been widely used and accepted as a robust method to search for the optimal solution to complex problems. In addition, investigators have accepted that GAs are better than other optimisation schemes (e.g. LP, NLP, and DP) in finding the global optimum (Reddy and Kumar, 2006; Azamathulla et al., 2008).

Thus the approach to hedging in this study will be based on traditional rule curves with both the critical rule curves and its associated hedging quantity determined using genetic algorithms (GA). GAs are a probabilistic search approach inspired by the principles of natural selection and evolution. They combine the concept of the survival of the fittest with genetic operators extracted from nature to form a robust search mechanism. The main challenge in standard GA optimisation, however, is establishing the optimum boundary of the feasible region to search for the optimal solution. Too wide a boundary will increase the computational time while too narrow a boundary may lead to the solution missing the global optimum (Purohit et al., 2013; Roeva et al., 2013). To solve this problem, a new development of the GA, known as the dynamic GA (DGA), that is more efficient and more rapid than the standard GA (SGA) in arriving at an optimal solution, has been developed.

A further dimension that complicates the reservoir operation task was alluded to earlier and concerns the inflow into the reservoir for each operational period. To base the water allocation on the total quantity of water available at the start of the period assumes that this quantity of water is known. However, while the starting storage is known, the inflow is an unknown quantity for which various assumptions have been made. These include that it is equal to the historic flow for the month under consideration or the historic mean flow for the month under consideration or the forecast flow for the month as obtained from a forecasting model. All these different inflow knowledge situations will have different impacts on reservoir performance that must be investigated. However, while the first two approaches for quantifying the inflow are easy to implement, the third will require the development to a forecasting model.

Consequently, the forecasting of this inflow into a reservoir is very essential. Several techniques have been used for reservoir inflow forecasting such as hydraulic (routing) method, time series analysis approach, rainfall-runoff modelling, regression analysis and artificial neural networks (ANN). This thesis does not cover in depth many forecasting technical issues as there is a plethora of text books on the subject. However, ANN is a flexible mathematical model capable of mapping most non-linear models. In addition, investigators such as Edossa and Babel (2012) and Mohammadi et al. (2005), have suggested that ANNs have the ability to forecast non-stationary time series data and that their performance is better than regression-based models and time series analysis, especially when they are not being used as extrapolators i.e. the range of prediction is limited to the network's experience and range of exemplars used for model training and validation. Consequently, ANN inflow forecasting models will be developed and applied in this study. Fuller details of ANN modelling are reviewed in Chapter 2.

The above clearly shows that better operational practices are required for reservoirs, especially if the alternative of additional resources' development to meet water scarcity is not feasible. While reservoirs are a major feature of any water supply system, relying exclusively on surface water resources, the planning of reservoirs takes too long time and its development involves huge financial and environmental costs, making new reservoir development unpopular. The use of hedging to redistribute water shortage has been proven, but the most common method of achieving this, i.e. by integrating hedging policies on the SOP, may be inappropriate given the tendency to hedge in regions of water scarcity. On the other hand, zone-based hedging, whilst more plausible because its hedging takes place when the system is operating normally, has hitherto been restricted to single zones without any investigation of the possible enhancements that multiple-zoning can have on reservoir system performance. Given the effects, which projected climate and other environmental changes are being suggested to have on water availability, an investigation of the additional benefits that multi-zone hedging can have on tempering such effects on water security will be very useful to reservoir operators worldwide. The need to develop such multi-zone hedging policies within an optimisation framework and evaluate its impact on reservoir performance to better inform operational decision making formed the main impetus of this study.

To demonstrate the applicability of the developed paradigms, the Ubonratana Reservoir in the upper Chi River Basin in northeastern Thailand has been selected as the case study. The choice of this reservoir system as a case study was influenced by a number of considerations. First is the availability of the needed data and its ease of access which has been made possible by the desire of both the Electricity Generating Authority of

Thailand (EGAT) and the Royal Thai Irrigation Department (RID) to have a more robust and effective operational regime for this major water resources infrastructure. A second reason concerns conflict that results when allocating scarce water resources and the need to have a system that eliminates periods of large water shortages thus ensuring that more water is available for allocation to most users. Drought is one of the most serious water resources problems in northeastern Thailand, due to the uncertainty in monsoon rainfall patterns. The resulting water scarcity affects the agricultural sector, which is the major economic activity in the region, hampering the rural economy and people's livelihoods. Indeed, agricultural production in northeastern Thailand relies heavily on irrigation and the Ubonratana reservoir is the main infrastructure regulating river flows for irrigation as well as other consumptive uses including municipal and industrial water supply, hydropower generation and low flows augmentation. Current practice for water allocation during such droughts is at best arbitrary because although there are existing rule curves, there are no hedging policies to guide the water rationing during extreme drought events. A third reason for the choice of the system is that existing rule curves formed the basis of the optimisation for the development of improved rule curves and its integrated hedging policies, making the implementation of the genetic algorithms optimisation much easier, as will be seen later on. Fourthly, given that the PhD study was entirely funded by the Royal Thai government, using a strategic national infrastructure as the Ubonratana as a case study is a way of ensuring good return on the investment by the government. Finally, flood control is also a major function of the reservoir which is catered for through a flood control curve. Although further optimisation of this flooding curve will not be attempted as part of the current study, the improvement in the normal rules curves through its optimisation and the integration of hedging is expected to enhance the capability of the reservoir to accommodate more flood water.

1.2 Aim and objectives

The aim of this work is to develop improved reservoir operation through optimised hedging-integrated rule curves and demonstrate its effectiveness in reservoir performance enhancement. The objectives are to:

(1) Review exhaustively the literature on reservoir planning and operation studies to identify good practices and knowledge gaps that can inform the development of the research methodology.

(2) Present the development of the new dynamic GA (DGA) optimisation and discuss its main features that distinguish it from the standard GA (SGA).

(3) Apply both SGA and DGA to the optimisation of hedging-integrated rule curves for the operation of the Ubonratana multi-purpose reservoir in Thailand.

(4) Develop artificial neural networks (ANN) models for monthly inflow forecasting at Ubontarana.

(5) Carry out extensive simulation of the Ubonratana reservoir to assess the performance impacts, if any, brought about by water hedging and various assumed inflow knowledge situations including forecasting.

1.3 Thesis outline

Chapter 1 provides the background for, and aim and objectives of, the study. It also outlines the structure of the thesis.

Chapter 2 is a review of the literature. It describes the general characteristics of reservoirs, the general concept of reservoir operating policy, defines and discusses procedures for reservoir performance evaluation and indices used, and describes the main characteristic of the reservoir system models. The optimisation techniques for reservoir operation control are also reviewed. The basic concept of developing an optimisation model to deal with the operation of water allocation is then described. The genetic algorithm for optimising the reservoir rule curves and hedging rules is reviewed. This chapter also discussed about the challenges of genetic algorithm. The introduction of reservoir rule curves and hedging rules are also presented to provide the basic idea for operating reservoirs. Finally, inflow-forecasting applications for reservoir management are reviewed. The artificial neural networks (ANN) approach and its structure are described.

Chapter 3 presents the methodological approach for the thesis. The standard genetic algorithm (SGA) parameters used are defined. The procedure of new dynamic genetic algorithm (DGA) and its key parameters are presented. The approaches of the simulation-optimisation reservoir model for rule curves and hedging rules are described. A general mathematical formulation for optimal reservoir operation including the major objectives, decision variables, and constraints is presented. Finally, the chapter presents the reservoir inflow-forecasting model based on the artificial neuron network method. The ANN approach and its structure are also described.

Chapter 4 describes the study area of the reservoir, the general characteristics of the river basin and these of the Ubonratana reservoir. The required data used in the study are also summarised. These include not only the hydro-met data but also the water demand and release data for the various purposes served by the reservoir-municipal water supply, irrigation and environment, the area-storage-height function for the reservoir and of course the existing reservoir operating policies.

Chapter 5 presents the results of the study in four sub-sections. First, the performance of existing policies at the Ubonratana reservoir including SOP are evaluated. Second, the results of optimised reservoir operating rule curves including the testing of the GA accuracy are presented. In this section, GA parameters i.e. population size, number of generations and repetition are determined. Third, the results of optimised single- and two-stage hedging-integrated rule curves are demonstrated. Fourth, the results of inflow forecasting using ANN is presented. The effect of inflow knowledge situations on the reservoir policies are also investigated.

Chapter 6 presents the analysis and discussion of the results.

Finally, Chapter 7 provides the main conclusions of the study and recommendations for future research work.

Chapter 2 Literature Review

2.1 Introduction

Rivers are one of the main water resources of water supply systems to satisfy water demand, such as municipal, industrial, irrigation, agriculture and transportation. When the water demands are lower than the flow in rivers, such demands can be satisfied by the natural flow. On the other hand, the natural flow cannot satisfy the demands when the flow in rivers is lower than the water demands. Therefore, water shortages can occur. When water shortages happen over a long period, water users suffer from drought or severe drought. Hence, designing and operating reservoirs to control and regulate the river flow are important aspects of water resource systems development.

This chapter reviews some of the general characteristics of reservoirs. The review begins in section 2.2 with a classification of reservoir systems. Both single and multi-reservoir systems are considered in the review. Reservoir storage zones are essential in the operation of reservoirs and generating the rule curves, and are described in the same section. The importance of the elevation-area-storage relationship, for the simulation especially in relation to the handing of the inclusion of net evaporation losses is presented in this section. In the next section (2.3), reservoir performance criteria are reviewed. The performance criteria are used to evaluate the effectiveness and efficiency of the reservoir systems. Section 2.4 reviews reservoir operation schemes which consist of a standard operating policy, rule curves and hedging rules. Their advantages and disadvantages are also discussed. In the next section (2.5), reservoir simulation models are reviewed. Common software tools for reservoir simulation models, such as WEAP, HEC3 and HEC5 are also reviewed in this section. The various optimisation approaches that have been applied for water resources management are reviewed in section 2.6. However, owing to the large body of literature on the subject, only approaches of direct relevance to the study are considered. Thus, the genetic algorithm (GA) optimisation approach and NLP that formed the basis of the optimisation in the study are also reviewed. The inflow forecasting techniques are reviewed in section 2.7. The artificial neural network is used in the study, so this technique is the main focus of literature in this section.

2.2 General characteristics of reservoirs

2.2.1 Classification of reservoirs

In general, there are two types of reservoir systems—single reservoir system (Figure 2.1) and multi-reservoir systems (Figure 2.2). Each type can function as either a single-purpose reservoir or multi-purpose reservoir. A single-purpose reservoir is designed for one purpose such as municipal water supply. In contrast, a multi-purpose reservoir has multiple functions including flood control, hydroelectric power, navigation, fish and wildlife enhancement and recreation. In addition, a multi-purpose reservoir functions to control irrigation, municipal and industrial water supply.

2.2.1.1 Single reservoir system

A reservoir which operates independently of one another to satisfy a given purpose, is called a single reservoir system. For example, Figure 2.1 shows a schematic diagram of the multi-purpose, single reservoir system and the various diversions of the Ubonratana reservoir in Thailand. Various heuristic operating policies for single reservoirs have been suggested such as pack rule (Mass et al., 1962), standard operating policy (Mass et al., 1962; Loucks et al., 1981), rule curves (Kaczmarek and Kindler, 1982) and hedging rules (Bower et al. 1966). The pack rule is briefly discussed later in this section; the others are discussed in section 2.3.

2.2.1.2 Multi-reservoir system

Reservoirs which cooperatively operate for one or more purpose are called a multi-reservoir system. Such a system can be in series (Figure 2.2 (a)), in parallel (Figure 2.2(b)) or a combination of both operating in parallel and series (Figure 2.2(c)). Due to significant storage possibilities, river basins are managed in multi- reservoir systems. As expected, the operation and planning analysis for multi-reservoirs is more complex than that for single reservoir systems (Lund and Guzman, 1996).

(i) Series multi-reservoir systems

Figure 2.2(a) illustrates a system of reservoir in series and consists of two reservoirs located on the same river; one downstream of the other. The common rule for operating multi-reservoirs in series is to deliver the water from the lowest (downstream) reservoir first, to meet demands. If it is not feasible, then additional water is taken by progressively moving to upstream reservoirs. In this way, there will be sufficient water to meet demand because any spills by upstream reservoirs will be captured by the space created in the downstream reservoir instead of being lost to the system (Lund and Guzman, 1999).

(ii) Parallel multi-reservoir systems

A system of two parallel reservoirs, as illustrated in Figure 2.2(b), consists of two reservoirs located on two different rivers which cooperate downstream of the reservoir, the downstream demands can be met by any one or both reservoirs. An important difference in the operation of series and parallel reservoir is that the release from an upstream reservoir cannot be captured by a downstream reservoir (Jain and Singh, 2003).

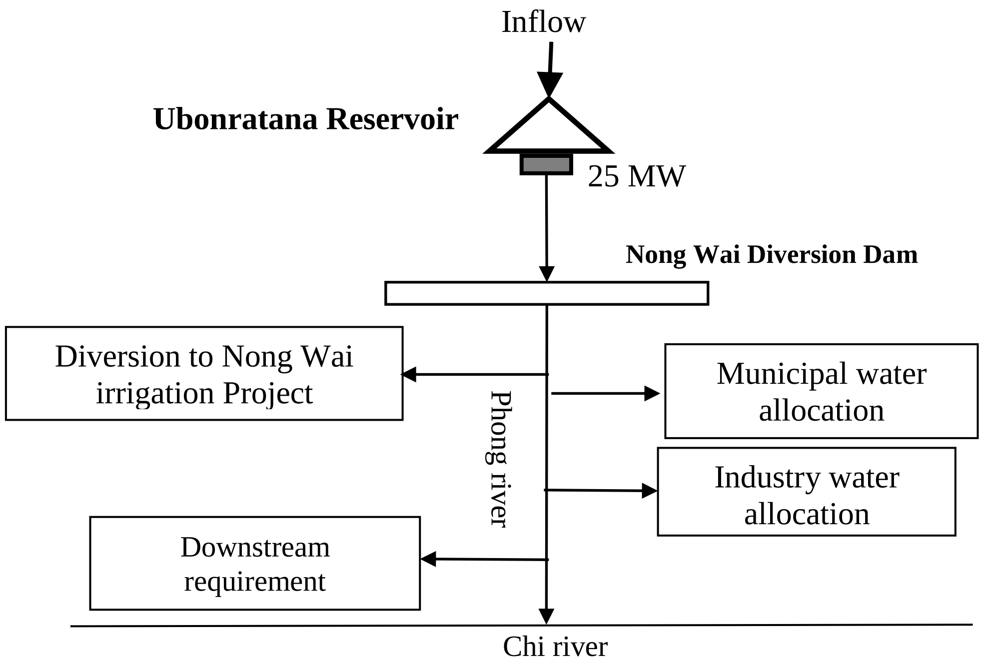
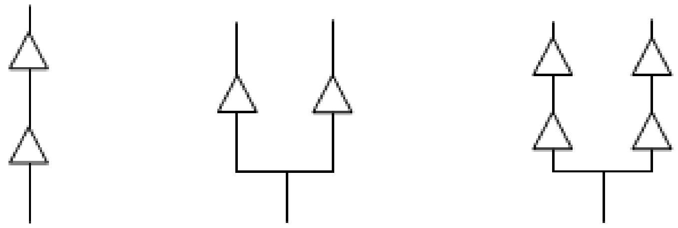


Figure 2.1 Schematic diagrams of a single reservoir at the Ubonratana reservoir (EGAT, 2002)



(a) (b) (c)

Figure 2.2 Schematics of (a) series, (b) parallel and (c) parallel and series multi-reservoir systems (McMahon and Adeloye, 2005).

(iii) Multi-reservoirs operations

For the water supply system in multi-reservoirs operation, classical operating rules such as hedging rule, space rule and pack rule have been widely applied. The detail of hedging rules will be described later in section 2.3.

(1) Space rule

In absence of any formal operating policy, which is the case during planning, the use of the space rule has been shown to minimise spill from each reservoir in a group of reservoir (Bower et al., 1966; Johnson et al., 1991). Space rules have been developed for water supply storage and energy storage purposes. For water supply purpose, the space rule is the approach that attempts to equalise the ratio of available space in each of the parallel reservoirs at the end of a period to the expected inflow into each reservoir during the remainder of the drawdown-refill season (Fang et al, 2014). In this way, application of the space rule avoids the inefficient condition that one reservoir is full and spills while another one remains unfilled (Maass et al., 1962). Once the apportioning of sequential deficits has been carried out, it is then straightforward matter to determine the proportion of the total demand during a period, which is to be met from each reservoir. For energy storage reservoir schemes, where refill is uncertain, spills represent wasted energy, and the use of the space rule will limit this waste. For example, to protect energy spills, Bower et al. (1966) discussed the use of the space rule to leave more space in reservoir where greater potential energy of inflows is expected.

(2) Pack rule

The pack rule specifies that whenever there is an excess of water, and releases beyond specified targets have some value, water available in excess should be released to realise those benefits (Oliveira and Loucks, 1997). The pack rule can be applied for the operation of both single and multi-reservoir systems. The pack rule can also be used for avoiding spills by additional releases of water in advance in order to make the reservoir space free for expected inflow that would otherwise spill (Mass et al., 1962). In Bower et al. (1966), the pack rule was applied for increasing hydropower generation by releasing the water beyond the target level to meet the hydraulic capacity of power plant in anticipation of surpluses.

2.2.2 Reservoir Storage Zones

Generally, reservoir managers are expected to maintain the storage level in the specified zones to maximise gain and minimise damage. This conceptual division of a reservoir into a number of zones is based on the assumption that, at a given time, an ideal storage zone exists for the reservoir and maximum benefits are achieved by maintaining the storage level in the appropriate zone (Jain and Singh, 2003). Reservoir storage generally consists of at least four storage zones — flood control zone, conservation zone, buffer zone, and inactive zone (Sharma and Sharma, 2007); these are illustrated in Figure 2.3.

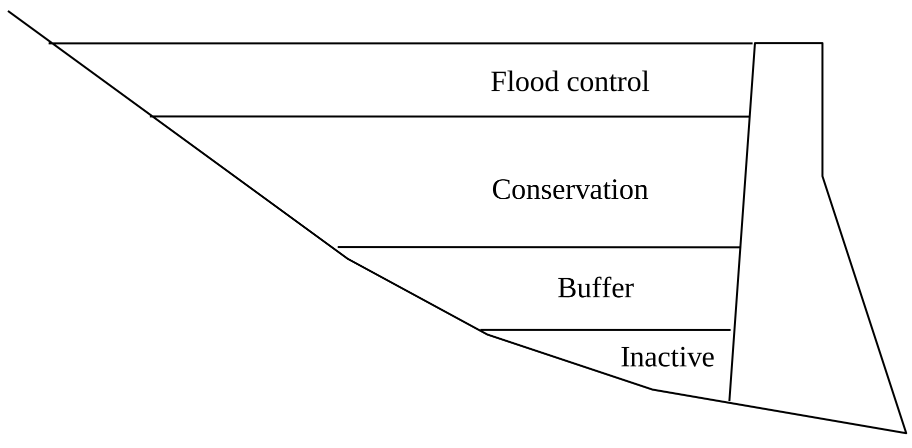


Figure 2.3 Zones of storage in a reservoir

The flood control zone is reserved for storing large inflows during heavy rainfall or high runoff periods. Therefore, an effective reservoir operation must ensure that the flood control zone is always available. Moreover, some reservoir policies define a spill or surcharge zone above the flood control zone. Therefore, when the storage volume reaches this zone during periods of extreme inflows, the reservoir releases and volumes are nearly at their maximum values. The conservation zone of storage volume is used to satisfy water demands and is usually the subject of reservoir design and planning analyses. The buffer zone is below the conservation zone and is used for storage only during severe drought periods. When storage volume enters this zone, discharges of water are strictly prioritised according to the most critical water demands (Kaczmarek and Kindler, 1982). Finally, the inactive zone or dead storage, which is below the buffer zone, is reserved for sediment deposits and ecosystems in the reservoir. Water in the inactive zone is not available for allocation, although in an extremely dry period evaporation may draw the storage into the inactive zone.

2.2.3 Elevation-Area-Volume Relationship

Figure 2.4 shows the elevation-area-storage relationship of the Ubonratana reservoir (EGAT, 2002). The relationship between water level elevations, the water surface area of the reservoir, and the storage volume is very important for reservoir operation. Due to hot dry air moving from the land surface, evaporation in a small shallow reservoir is higher than that in a large deep reservoir (Sivapragasam et al., 2009). Selecting a deep narrow valley for a reservoir site can thus minimise loss of water by evaporation (Geddes and Campbell, 2015). Therefore, the elevation-area-volume relationship provides important information for the development of a reservoir because it assists in selecting the most appropriate site to reduce evaporation loss. Evaporation loss is especially important in tropical regions because it can be so large that it affects the ability of the reservoir to meet its target. Its consideration must therefore be included in plaining analyses to avoid significant under-sizing of the reservoir (Kenabatho and Parida, 2005).

The elevation-area-storage relationship is required for calculating the volumetric evaporation loss from the surface of the reservoir during planning analyses, as described below (Adeloye et al., 2001). The basic equations in a reservoir operation are the continuity equation (mass balance) and the reservoir state equation. The water balance equation states that for a time period the inflow minus the outflow equals the change in storage, i.e.

$$\text{Inflow-Outflow} = S_{t+1} - S_t \tag{2.1}$$

where, S_{t+1} is equal to the storage at the end of the time period and S_t is the starting storage

Hence for a given time interval t, in which the inflow is Q_t and total outflow is O_t from a reservoir of size Ka. Equation 2.1 will become:

$$S_{t+1} = S_t + Q_t - O_t\,;\quad 0 \le S_{t+1} \le Ka \tag{2.2}$$

S_{t+1} in Equation (2.2) has a lower limit of zero i.e. an empty reservoir and an upper limit equal to the storage capacity of the reservoir Ka, i.e. the storage cannot be larger than the physical size of the reservoir. The outflow can be differentiated into useful outflow satisfying a demand (D_t), spilling (Y_t) and losses (L_t). Spilling only occurs when the reservoir is full and the main loss is the net evaporation (evaporation-rainfall) from the reservoir surface (E_t).

Hence Equation (2.2) can be expressed as:

$$S_{t+1} = S_t + Q_t - D_t - E_t - Y_t\,;\quad 0 \le S_{t+1} \le Ka \tag{2.3}$$

However, because both evaporation and rainfall are normally measured in mm, the net evaporation cannot be used directly in Equation (2.3). It must first be converted to volume of water by multiplying by the surface area (A_v) of the reservoir in interval t i.e.

$$S_{t+1} = S_t + Q_t - D_t - e_t A_v - Y_t \tag{2.4}$$

where e_t is the net evaporation in interval t (i.e. evaporation – rainfall) measured in equivalent depth of water loss during the interval.

As seen in Figure 2.5 the surface area of a reservoir depends on the storage: as the storage increases, so does the exposed surface area, albeit in a non-linear manner. However, for planning purposes, a linear approximation to the area-storage relationship is often assumed (see Figure 2.5), i.e.

$$A_t = aS_t + b \tag{2.5}$$

where, *a* and *b* are coefficients which can be obtained by fitting a regression equation to the available area-storage data. The area A_v for a time interval can then be represented by the average of its value at the beginning and end of the interval as follows

$$Av_t = (A_t + A_{t+1})/2 = 0.5(aS_t + b + aS_{t+1} + b) = b + 0.5a(S_t + S_{t+1}) \tag{2.6}$$

Combining Equations (2.4) and (2.6), and nothing that spill Y_t does not occur during the low inflow period when evaporation is important and re-arranging gives the final expression for the balance of reservoir contents incorporating evaporation losses as:

$$S_{t+1} = (S_t(1 - 0.5ae_t) + Q_t - D_t - be_t)/(1 + 0.5ae_t) \tag{2.7}$$

Equation (2.7) is the basis of reservoir planning analysis using behaviour simulation and includes a consideration of net volumetric evaporation loss explicitly. If, for whatever reason, evaporation is unimportant or there are no evaporation data, then e_t = 0 and Equation (2.7) will degenerate to the simple form in Equation (2.3) (without the evaporation term).

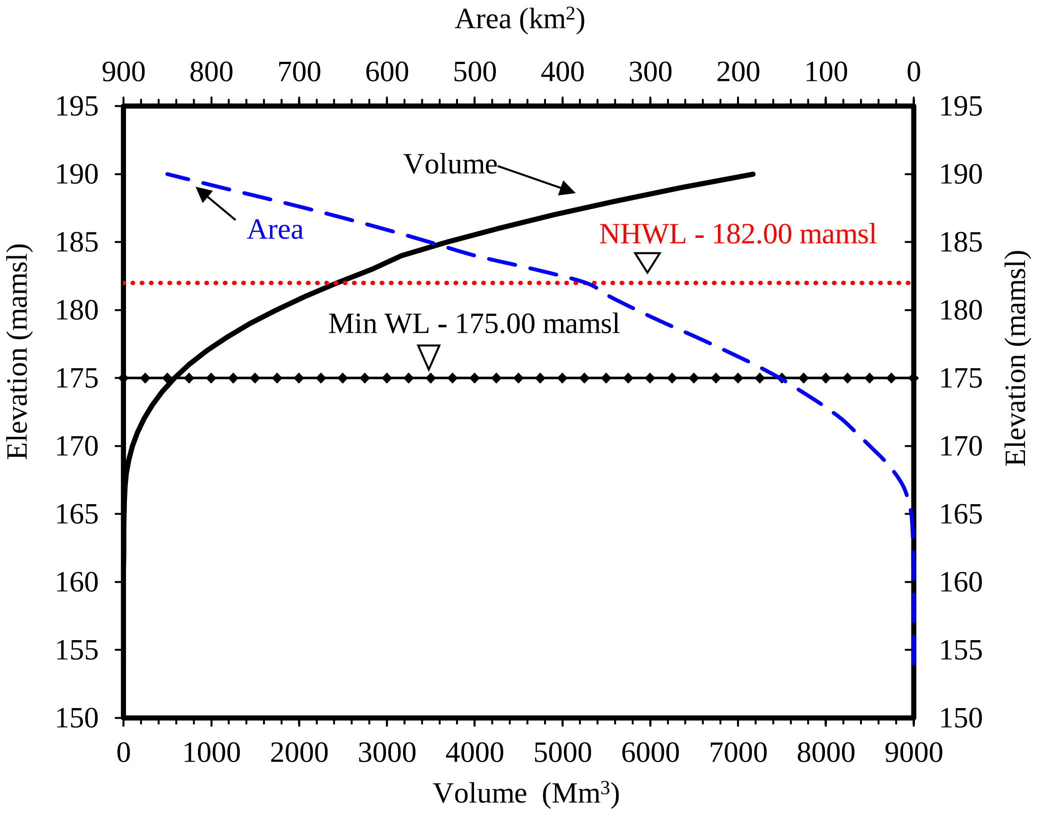


Figure 2.4: The elevation-area-storage relationship of the Ubonratana reservoir (EGAT, 2002)

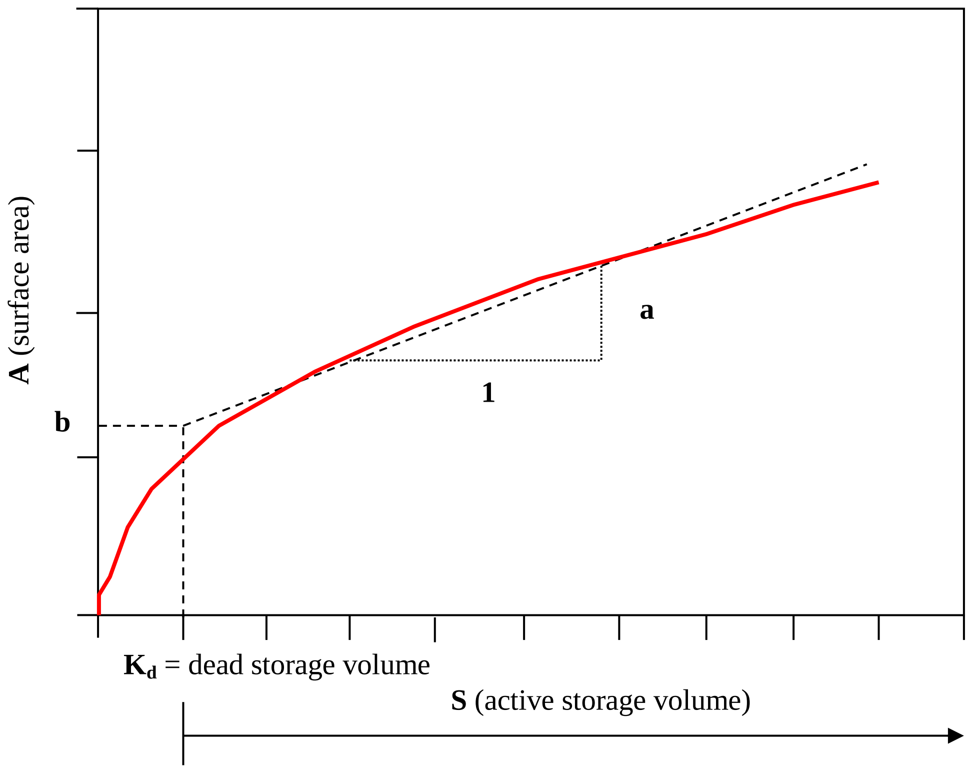


Figure 2.5 Approximate linear are-storage relationship

2.3 Reservoir system performance criteria

A reservoir is used to satisfy various water demands and manage water resources. Effective reservoir management requires performance measures to evaluate the effectiveness and efficiency of the systems. Thus, performance measures are a significant aspect of planning and operating reservoir systems (McMahon and Adeloye, 2005; Adeloye, 2012). The performance criteria are used to define and measure a failure or an unsatisfactory operation of the reservoir system. In addition, they are also used to evaluate reservoir operating policies or to compare alternative policies (Sandoval-Soils et at., 2011). The reservoir is unable to meet the full demand at all times. In practice, a certain level of water shortage is acceptable because building a reservoir with capacity of no failure level is very expensive. The performance measures include time-based reliability (annual, monthly), volumetric reliability, resilience, vulnerability and sustainability index and are presented as follows.

2.3.1 Reliability

The reliability concept defines the probability that the available water in a reservoir will be able to meet the target demand in any particular time interval within the period of simulation (Sandoval-Soils et al., 2011; McMahon et al., 2006).

(i) Time-based reliability is the portion of time periods during the simulation period that the water demand is fully supplied. The time-based reliability can be expressed as follows (McMahon and Adeloye, 2005):

$$R_t = \frac{N_s}{N} \tag{2.8}$$

where R_t is time-based reliability (dimensionless); N_s is the total number of time periods during which the demand was met; N is the total number of time periods in the simulation analysis.

The time-based reliability is easy to determine and use; however, it does not distinguish between a failure involving large quantity and a failure with very little quantity. Hence the need for the volume reliability.

(ii) Volumetric reliability is computed as the total quantity of water actually supplied divided by the total quantity of water demanded during the simulation period. The volumetric reliability can be expressed as follows (McMahon et al, 2006):

$$R_v = \frac{\sum_{t=1}^{N} D'_t}{\sum_{t=1}^{N} D_t} \quad ; 0 \leq R_v \leq 1 \tag{2.9}$$

where R_v is the volumetric reliability; D_t is the target demand during t^{th} period; D'_t is the volume actually supplied in the period; N is the number of time intervals in the simulation. If the demand is satisfied in all the time periods, then $D'_t = D_t$ for all t and R_v is unity.

It should be noted that R_v will always be equal to or greater than R_t because of the differential weighting of shortages in R_v. Observations on the volumetric reliability may be made to adjust further time-based reliability, e.g. the time-based reliability may be relaxed if the volumetric reliability is very high or made more stringent if the volumetric reliability is too low (Adeloye, 2012).

2.3.2 Resilience

Often it is necessary to known how readily a reservoir system will recover following failure. Resilience is a measure of the reservoir's ability to recover from failure. Several definitions have been used for resilience (Fiering, 1982); however, the most widely used one is attributable to Hashimoto et al. (1982). They defined resilience as the probability that a reservoir system will recover following a failure, expressed as follows:

$$\varphi = \frac{1}{\frac{fd}{fs}} = \frac{fs}{fd} \quad ; 0 < \varphi \leq 1 \tag{2.10}$$

where φ is resilience; f_s is number of continuous sequences of failure periods; f_d is the total duration of the failures.

Therefore, if the resilience is close to or equal to one, the system is highly likely to recover from failure and return to a satisfactory state. On the other hand, if the resilience is very low or close to zero, due to a longer failure duration or a fewer number failure sequences, the system will have more difficulty in recovering to a satisfactory state.

The resilience can be defined by another expression which is the maximum number of consecutive deficit periods prior to recovery (Sandoval-Soils et al., 2011).

$$\varphi = \frac{\text{No. of times } TS_t{=}0 \text{ follow } TS_t{>}0}{\text{No. of times } TS_t{>}0 \text{ occured}} \tag{2.11}$$

where φ is the probability that a successful period follows a failure period for all failure periods; TS_t is deficit (or total shortage) in time t.

Although Equation (2.11) uses deficits, it is essentially the same as Equation (2.10) when evaluated. This is because the denominator in Equation (2.11) gives the number of occasions of non-zero deficits, which is nothing more than the f_d in the denominator of Equation (2.10). Similarly, the numerator in Equation (2.11) is the number of sequences of continuous failures, f_s.

As noted before, there are other definitions of resilience in the literature. For example, Vogel and Bolognese (1995) characterised the resilience, using Hurst's standardized demand:

$$\varphi = m = \frac{1-\alpha}{\mathrm{Cv}} \tag{2.12}$$

where m is Hurst's standardized net inflow parameter; α is annual target demand (expressed as ratio of the mean annual runoff at the reservoir site, i.e. $\alpha = \frac{D}{\mu}$ where D is the volumetric demand and μ is the mean annual runoff); *Cv* is coefficient of variation (i.e. standard deviation divided by the mean) of annual runoff.

Vogel and Bolognese (1995) claimed that when m>1, the reservoir system will behave like a within-year system whose short critical period will ensure that it rapidly recovers following a failure. The larger the departure of m from unity, the more is the significance of the within-year or over year characteristics. On the other hand, when the m<1, the behaviour will be over year and the reservoir will be less resilient in that it will take a long time to recover following failure. The advantage of using '*m*' is that there is no need to carry out an expensive simulation of the reservoir system to estimate resilience as is required by Equation (2.10). However, Montaseri and Adeloye (1999) have found that the use of the index *m* as an indicator of the likely behaviour of reservoir system is incomplete because it ignores other parameters of the reservoir storage-yield problem that also influence reservoir behaviour. In particular, they found that the simulated critical periods for reservoir were often incompatible with those to be expected from the use of the index *m* alone.

Another measure of resilience, which is much easier to estimate than the measure in Equation (2.26) if the demand is constant, was suggested by McMahon et al. (2006):

$$\varphi = \frac{\breve{D}'}{D} \tag{2.13}$$

where $\breve{D}'$ is the minimum release in the failure periods; D is the target demand. Equation (2.29) is the ratio of the minimum release to the demand. If this ration is very low, because $\breve{D}'$ is very low, it means that the system is performing unsatisfactorily and the likelihood of it recovering early after a failure is going to be very low, i.e. low resilience. Conversely, a high value of $\breve{D}'$ will imply that conditions are not as serious and so the likelihood is that the reservoir system will soon return more quickly to normalcy (i.e. high resilience).

2.3.3 Vulnerability

Reliability measures say nothing about how quickly a system recovers and returns to a satisfactory value, nor do they indicate how bad an unsatisfactory value might be should one occur. It may well be that a system that fails relatively often, but by insignificant amounts and for short durations, will be much preferable to one whose reliability is much higher but where, when a failure does occur, it is likely to be much more severe. While the volumetric reliability indicates the proportion of the volume of demand satisfied, the vulnerability measures the average volumetric severity of the failure itself (McMahon et al., 2006). Consider f_s sequence of continuous failure periods in the reservoir simulation. Vulnerability is expressed variously as follows:

(1) The vulnerability is the average failure expressed as (Loucks and Beek, 2005):

$$\eta = \frac{\sum_{t=1}^{f_d}(D_t - D_t')}{f_d} \tag{2.14}$$

where D_t is the target demand during t^{th} period, D'_t is the volume actually supplied in the period, f_d *is the total duration of the failures.*

(2) The vulnerability definition adopted here is the average of the maximum shortfalls during each of the continuous failure sequence (Hashimoto et al., 1982)).

$$\eta' = \frac{\sum_{k=1}^{f_s}\max(shk)}{f_s} \tag{2.15}$$

where η' is vulnerability (volumetric unit); η is the dimensionless vulnerability metric; max(shk) is maximum shortfall during each continuous failure sequence; f_s is sequence of continuous failure periods in the reservoir simulation.

or in dimensionless form, assuming constant demand (McMahon and Adeloye, 2005):

$$\eta = \frac{\eta'}{D};\ 0 < \eta \leq 1 \tag{2.16}$$

If the target demand, *D*, is not constant, the dimensionless vulnerability becomes:

$$\eta = \frac{\sum_{k=1}^{f_s} \left(\frac{\max(shk)}{D_k}\right)}{f_s} \tag{2.17}$$

where D_k is the target demand during the k^{th} continuous failure sequence

(3) The vulnerability can be the average period shortfall as a ratio of the average period demand (Sandoval-Solis et al., 2011), when *D* is not constant; the vulnerability can be expressed as:

$$\eta = \frac{\sum_{t=1}^{f_d} [(D_t - D_t^{'}) / D_t\ ]}{f_d};t \in f_d \tag{2.18}$$

where D_t is the target demand during t^{th} period, D'_t is the volume actually supplied in the period and f_d is the total duration of the failures.

Other definitions of vulnerability have been adopted such as the maximum period deficit of water during the simulation by Moy et al., (1986) which is similar to Equation (2.15), apart from the averaging in Equation (2.15) whose effect will be to modulate the vulnerability. Nevertheless, the definition adopted by Moy et al., (1986) was convenient for their linear programming reservoir optimisation model. However, while all of these measures may be investigated in any particular application, it is felt Equation (2.17) and (2.18) is very simple and attractive to use and should be adopted.

2.3.4 Sustainability index

As presented earlier, the reliability, resilience and vulnerability have been adopted to evaluate the reservoir performance. However, some researchers have attempted to introduce a single index which contains the combined the effects of these indices.

Zongxue et al. (1998) combined the concepts of reliability, resilience and vulnerability to produce a single metric termed the drought risk index (DRI), which is dimensionless and is defined as:

$$DRI = \xi_1(1-R_t) + \xi_2(1-\varphi) + \xi_3\eta \; ; \; 0 \leq \mathrm{DRI} \leq 1 \tag{2.19}$$

When $\xi_1 + \xi_2 + \xi_3 = 1$

where $\xi_1, \xi_2 and \xi_3$ are weights that may be assigned depending on the relative significance placed by the analyst on each of the three performance indices. If the three indices are weighted equally, then $\xi_1 = \xi_2 = \xi_3 = 1/3$. Where the vulnerability is the overriding consideration, then more weight can be given to ξ_3 relative to other two weights. However, a difficulty with DRI is in choosing the relative weights.

Later, there have been a number of approaches defining sustainability of reservoir systems; however, the only quantitative measure is the sustainability metric of Loucks (1997) which combines the three measures reliability, resilience and vulnerability ratio—to develop a sustainability index thus:

$$\lambda = R_t\varphi(1-\eta) \qquad ; \; 0 < \lambda \leq 1 \tag{2.20}$$

where λ is sustainability. Equation (2.20) is intuitively correct because the sustainability of a reservoir system increases the greater the reliability and resilience, and the smaller the vulnerability. The use of multiplication in Equation (2.20) serves a similar purpose to the weights used in DRI that it gives an added weight to the statistical measure having the lowest value (Loucks, 1997). In Equation (2.20), the result of λ will be high if all performance criteria have high values. However, this implicitly gives too much weight to the worst index, e.g. if any of the indices R_t, φ and $(1-\eta)$ is very low, the resulting λ will also be very low. The extreme case is what could be termed the "nullity" problem, in which if any of the constituent indices is zero, λ will also be zero irrespective of the values of the remaining indices.

A modification of Equation (2.20) was recently proposed by Sandoval-Solis et al. (2011), which partially overcomes this problem by using the geometric mean as follows:

$$\lambda = [R_t \ \varphi \ (1-\eta \ )]^{1/3} \tag{2.21}$$

According to Sandoval-Solis et al. (2011), the new index satisfies the properties of the λ defined by Loucks (1997), but, in addition, it has the following improvements:

Content: It allows the inclusion of other criteria of interest according to the necessities of each case. λ is no longer a fixed performance criteria related to water quantity; performance criteria of water quality and environmental performance might be included in λ.

Scaling: The use of the geometric average scales the values of λ, generating numbers that can be more practical to interpret and communicate. If a certain water user has a reliability, resilience, and vulnerability of 50% for each performance criterion, then λ calculated with Equation (2.20) and the proposed index Equation (2.21) are 13% and 50%, respectively. The scaling of λ does not obscure poor performance; its only purpose is to scale the values and make the index more practical and intuitive.

Flexibility: Several structures for λ might be applied in the same basin for different groups of water users or types of use. For instance, λ for municipal or recreational water use may include different performance criteria than λ for agriculture water use. Sustainability does not mean the same thing for all water users, and the proposed index allows it to be adjusted to suit the user or use of water.

Recently, Adeloye et al. (2016) proposed an alternative definition of sustainability index using R_v instead of R_t in Equation (2.21), because R_v, unlike R_t is less likely to be dramatically affected by water scarcity, as expressed;

$$\lambda = [R_v \, \varphi \, (1-\eta)]^{1/3} \tag{2.22}$$

Where several users' groups are involved, Equation (2.21) or (2.22) can be determined for each group or combined to form a global index using Equation (2.23) (Sandoval-Soils et al., 2011). The λ_G is used to calculate the sustainability for a group k that contains water user from i^{th} to j^{th}:

$$\lambda_G^k = \sum_{i=1\in k}^{i=j\in k} w_i \times \lambda_i \quad ; 0 \le \lambda_i \le 1 \tag{2.23}$$

Where w_i is the weighting for user i of a group k. A reasonable estimate of the weight is the proportion of the global annual demand due to each user group. Hence λ_G becomes:

$$\lambda_G = \sum_{i=1}^{i=j} \frac{water demand_i}{total water\ demand} \times \lambda_i \tag{2.24}$$

Finally, other more qualitative measures of sustainability have been proposed including fairness (Lence et al., 1997), reversibility (Fanai and Burn, 1997), and consensus (Simonovic, 1998). These criteria have been developed for sustainable water resources decision-making but given their qualitative nature, they are rarely used in quantitative water reservoir simulation studies (McMahon and Adeloye, 2005).

2.4 Single reservoir operation

2.4.1 Standard operating policy (SOP)

The standard operating policy is the simplest reservoir operating policy (Draper and Lund, 2004) and the most convenient to apply (Rittima, 2009) because the release rate depends on the demand and available water. However, this rule is scarcely used for actual reservoir operation because by nature it can result in large, single period shortages (Lund and Guzman, 1996).

As stated earlier in chapter 1, Figure 1.1 illustrates the SOP that defines three possible cases for the release of water in storage (Adeloye et al, 2001);

Case A (insufficient water): For $S_t + Q_t < D_t$,

$$D'_t = S_t + Q_t$$

(i.e. supply all available water and leave reservoir empty)

Case B (sufficient water): For $D_t < S_t + Q_t < D_t + Ka$,

$$D'_t = D_t$$

(i.e. supply target demand)

Case C (more than sufficient water): For $S_t + Q_t \geq D_t + Ka$,

$$D'_t = S_t + Q_t - Ka$$

(i.e. oversupply target demand and leave reservoir full)

where S_t is the storage at the beginning of t, Q_t is the inflow during t, D_t is the demand during t, Ka is the active storage capacity, and D'_t is the actual release during t.

Thus, the SOP not only allows the reservoir to be empty which is unacceptable, it also as a consequence generates large, single period shortages, especially during a period of persistent low flows into the reservoir. As clearly demonstrated by Adeloye et al. (2001) releases during such periods are limited in extreme cases to the inflow, implying no inflow, no release. Several research studies (e.g. Srinivasan and Philipose, 1996; Taghian et al., 2013) have attempted to solve these problems of the SOP by integrating hedging rules that deliberately reduce the amount of water supplied even when there is enough water. The hedging rules are reviewed later in section 2.4.3.

2.4.2 Rule curve

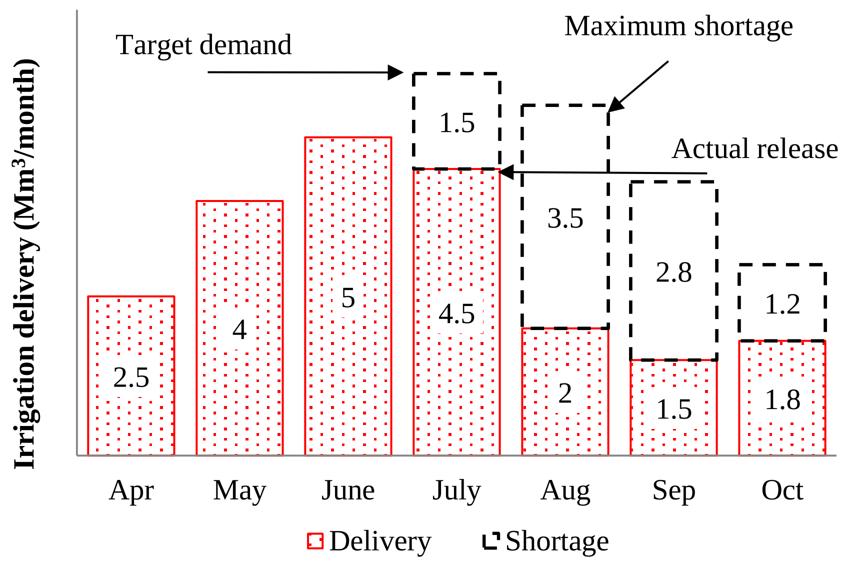
As noted earlier, problems associated with formalised reservoir operating policies such as the SOP have led most reservoir operators to rely on the use of heuristic rule curves to guide reservoir operation. Rule curves define ideal or target storage volumes or levels in individual reservoirs throughout the year, usually by month, but do not vary from year to year (Kaczmarek and Kindler, 1982). This means that reservoirs are operated under the same policy from one year to the next. When the actual storage level is less than the target volume, releases are reduced to prevent the reservoir from becoming empty, a situation which would aggravate future shortages (Jiang, 2011). On the other hand, additional water can be released if level exceeds the target.

Figure 1.2 in chapter 1 shows an example rule curves, which can be used to illustrate how rule curves help in guiding reservoir operation. Conventionally, there is only one curve, the upper rule curve (B) in Figure 1.2, which is below the reservoir top of flood control (A) and must be kept this way to accommodate possible flood surcharges. The top of flood control (A) defines the reservoir crest level of the spillway. Thus, if the reservoir level is at or above the upper curve (B), the demanded water or possibly more must be released to restore the storage to the level dictated by the control curve (McMahon and Adeloye, 2005). If the storage is below the curve (B), however, restriction in the volume of water supplied is warranted. The latter situation is the main problem with the use of rule curves; while it might indicate when reductions in the amount of water supplied are warranted, it does not provide guidance on the quantity of the reduction. Adeloye et al. (2003) developed rule curves with an integral attribute of specified shortages or vulnerability using the modified sequent peak algorithm (Adeloye et al., 2001), which defines the level of allowed cutback as a way of removing the limitations of traditional rule curves. Subsequent simulation of the reservoir with the hedging integrated curves eliminated occasions in which the reservoir was empty and caused the overall reservoir performance to improve.

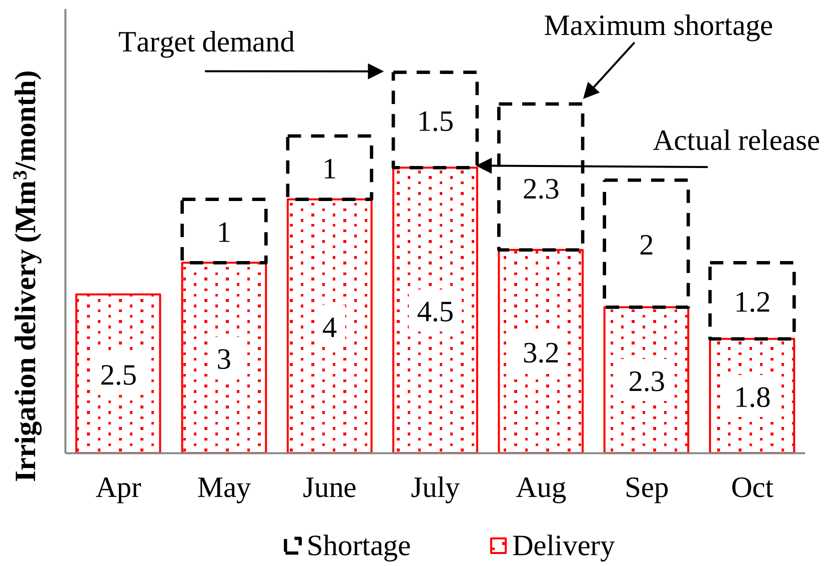
Another solution that has been widely adopted to solve the lack of guide on appropriate release reductions for single line rule curves is to develop upper rule curve (URC) and lower rule curve (LRC) such as curves (B) and (C), respectively, in Figure 1.2, with the proviso that when the reservoir level is within the space enclosed by the two curves, full demand could be met. The URC (B) defines the maximum level for flood control purposes, and the LRC (C) defines the limit for conservation purposes. The objective of the operation is to restore the reservoir level to the lower curve (C) by reducing the supplied water or to the URC (B) by oversupplying the demand. Thus in Figure 1.2, when the level of water available in storage is between curves (A) and (B), water is released to supply full demand to the maximum extent possible without causing flood damage. Conversely, when the level of water available in storage is below curve C, water allocation would be reduced as much as possible for low priority water uses but maintained for high-priority uses. The curve D defines the dead storage, and is called the minimum water level (Min.WL). Thus, when the storage level is below curve D, no water is supplied.

2.4.3 Hedging rule

As outlined in section 2.4.2, reservoir operation using the SOP and traditional rule curves save no water for impending droughts, and the consequential shortage during such droughts can be very large. This problem can be tempered by water rationing during normal operational periods, i.e. rather than supplying the full demand, the supply is curtailed usually by moderate amounts and the saved water can be used to limit the amount and impact of water shortages during droughts (You and Cai, 2008a; 2008b; Tu et al. 2008; Eum et al. 2011; Draper and Lund, 2004). This practice is known as "hedging" (Bower et al. 1982). Hedging policies reduce the number and volume of large shortages by increasing the frequency of small shortages (Srinivasan and Philipose, 1996).



(a)



(b)

Figure 2.6 Monthly deliveries and shortages for irrigation delivery (a) without hedging policy and (b) with hedging policy (Bower et al., 1966).

A schematic illustration of the water rationing concept and its effect on the maximum single period shortage for the irrigation sector is shown in Figure 2.6(b), with Figure 2.6(a) depicting no rationing operation. The total water shortage over the 7-month period is equal to 9 units for both situations. However, the maximum single period shortage or vulnerability with no hedging was much larger than the corresponding hedging value. In particular, the effect of the hedging rule decreased the vulnerability from 3.5 units to 2.3 units, a fall of 34%. This large reduction in vulnerability was achieved through a proportionally lower (22%) curtailment in normal period deliveries.

Practically, reservoir managers need to know when to hedge for a given reservoir with a specified target yield (Srinivasan and Philipose, 1998). The main challenge in hedging, therefore, is establishing the timing and amount of the rationing since the inability to establish these correctly may be counterproductive. For example, too little rationing may not solve the crippling water shortage problem during future droughts, while too much rationing may turn out to be unnecessarily punitive. The amount of water available will also be affected by net evaporation (i.e. evaporation minus rainfall) losses (Booker and O'Neill, 2006; Montaseri and Adeloye, 2004); thus the explicit inclusion of net evaporation losses in reservoir mass balance (as shown in Section 2.2.3- see also Adeloye et al., 2001) is important, especially in catchments for which the evaporation rates are higher than the precipitation rates (Nawaz et al., 1999). This is because higher evaporation rates and larger increases of reservoir surface area with storage (reservoir topology) will aggravate the effect of evaporation loss on the marginal values of water in the current and future periods. Integrating a system of water hedging to operating policy has been attempted using one of two approaches: SOP-based and Zone-based.

2.4.3.1 SOP-based approach

A way the hedging problem has been traditionally approached is to develop hedging by modifying the standard operating policy (SOP); hence it is called the SOP-based approach. Several forms of hedging rules have been employed in SOP such as one-point hedging, two-point hedging, three-point hedging, continuous hedging, and multi-point hedging as seen in Figure 2.7. The implementation of these hedging forms is described by Lund and Guzman (1996) and Draper and Lund (2004). In one-point hedging, the release reductions begin at the origin and increase linearly (at slope < 1) until intersecting with the target release at P2. Two-point hedging begins at P1 and ends at P2, where hedging is no longer applied. Three-point hedging adds an intermediate point, P3, which is used in conjunction with P1 and P2 to introduce two linear portions. In continuous hedging, the slope of the hedging portion of the rule can vary continuously (Hashimoto et al. 1982). Multi-point hedging is a different discrete phased hedging rule controlled by beginning storage and starts at point a (Neelakantan and

Pundarikanthan,1999). The hedging factors of this concept are discrete proportions for different zonal levels where point b, c, d are the starting point of changing phase.

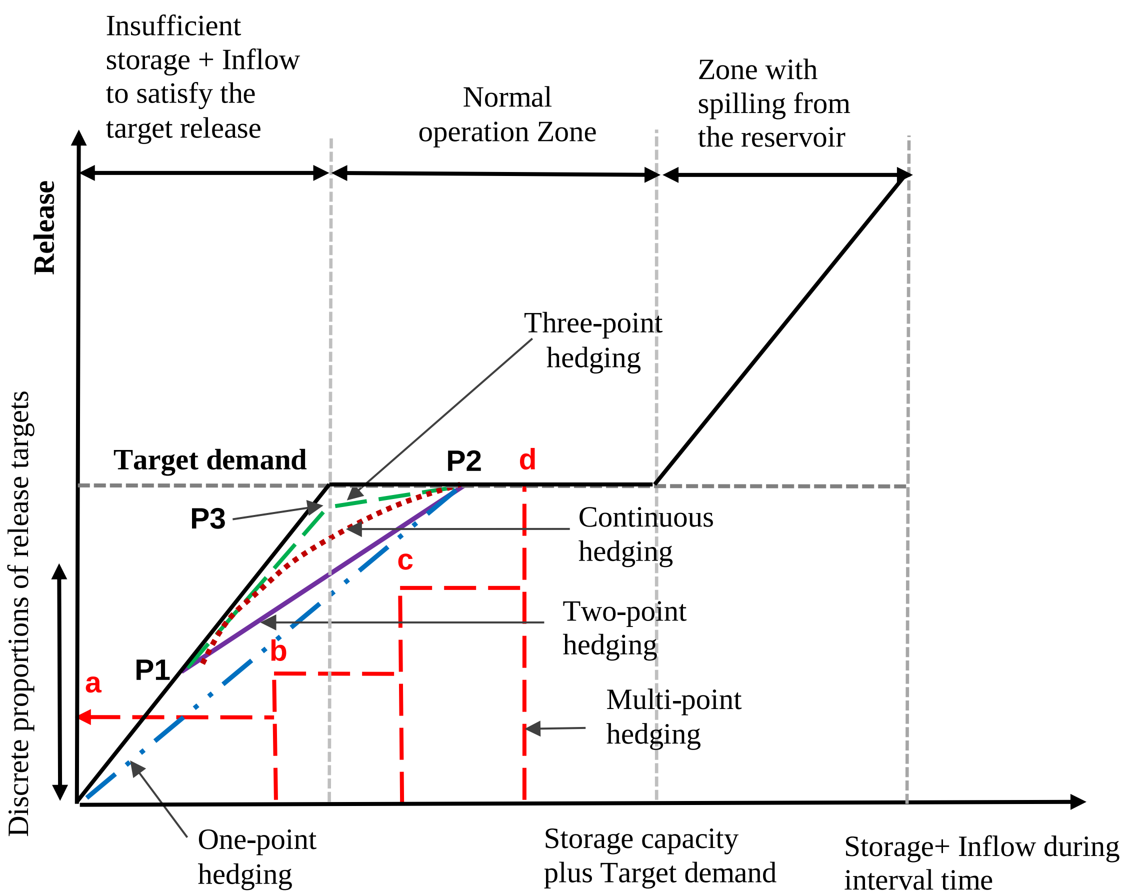


Figure 2.7 The SOP is modified by the hedging rule forms

The main issue in SOP-based hedging is the determination of onset (e.g. P1), end (e.g. P2) and the intensity (i.e. slope) of the hedging. Several investigators (e.g. Srinivasan and Philipose, 1996, 1998; Taghian al., 2013; Bayazit and Unal, 1990; Shih and ReVelle, 1995; Neelakantan and Pundarikanthan, 1999; Tu et al., 2008; Shiau, 2009, 2011) have researched this with different outcomes. For example, Shih and ReVelle (1995) applied a multi-point hedging rule in SOP and determined the starting point of hedging (with a given rationing ratio) under the objective function of maximisation of the number of periods without rationing. The study selected the most severe low flow which occurred in a 36-month period of the total 86 years' streamflow record. The result of the study guided the reservoir manager as to when to start hedging. However, this study deals only with a single drought, thus it was suggested to extend the procedure to multiple droughts in order to capture the variability of inflow sequence.

Srinivasan and Philipose (1998) investigated the effect of two-point hedging on over-year reservoir performance. Various hedging rules were tested using combinations of three parameters i.e. hedging start point, hedging end point and degree of hedging. Their study demonstrated that the time-based reliability decreased when the hedging end point increased because it increased the number of shortfalls. Increasing the degree of hedging has a tendency to increase the resilience because it results in increase of storage which helps in cutting down the continuity of shortfalls.

The hedging is implemented not only in a single reservoir system but also in multi-reservoir systems. For example, Neelakantan and Pundarikanthan (1999) presented a neural network-based simulation-optimisation model to develop multi-point hedging rule in SOP to improve multi-reservoir operation for drinking water supply management in Chennai city (India). Four reservoir storage zones were formed between empty storage and full storage with a fixed hedging factor for each level under the objective function of minimisation of the sum of squared deficits. Two way of storing water were tested: (1) storing water and filling water from the upstream reservoir first and (2) storing water in all reservoirs in proportion to their capacities. The results demonstrated that the way of storing and filling water from upstream is more appropriate than another way because it gives a lower objective function value than another way of storing water. However, they considered only the total deficit value to select an appropriate method and did not determine other performance indices such as the vulnerability, resilience and sustainability.

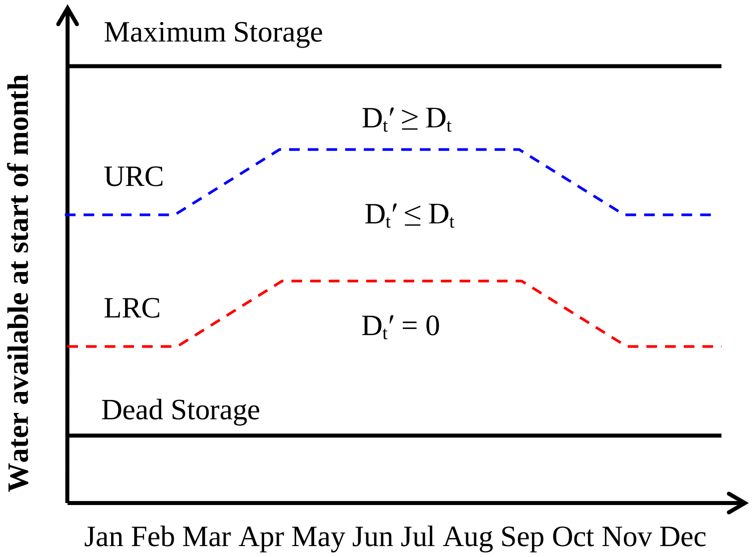
Bayazit and Unal (1990) investigated the effects of two-point hedging on reservoir performance related to hedging parameters i.e. the start (P1) and end (P2) points of hedging as seen in Figure 2.7. The time-base reliability and resilience were significantly reduced more than 80% when P2 was increased from the target demand to the storage capacity plus the target demand, i.e. hedging is implemented for much longer. However, the effect of changing P1 on the time-base reliability was not significant: it was only slightly decreased when P1 was close to the target demand i.e. the onset of hedging was delayed. The smallest value of mean deficit was obtained when P1 was close to the target demand and P2 was close to half of the shortage plus target demand.

Relatively recently, Shiau and Lee (2005) proposed an optimal two-point SOP-based hedging rule using multi-objective programming for minimising two conflicting shortage characteristics simultaneously i.e. short- and long-term water shortage. The results of their study indicated that ending hedging as late as possible and not starting too early can minimise the maximum monthly shortage. This is because when the hedging starts too early, it is bound to coincide with periods of insufficient water, thus making the water shortage situation worse and ultimately contributing to aggravating the vulnerability or single-period large shortages. On the other hand, extending the end date will ensure that most of hedging in the SOP-based approach takes place in the normal operation zone (see Figure 2.7) of the reservoir. Although this will increase the number of small shortages, which as explained earlier will cause the time-based reliability to worsen considerably, the more important volume-based reliability will be not largely affected. To obtain the total amount of water available, the study proposed the use of deciles of monthly inflows instead of inflow forecasting and assumed the reservoir evaporation losses to be negligible in their water balance equation.

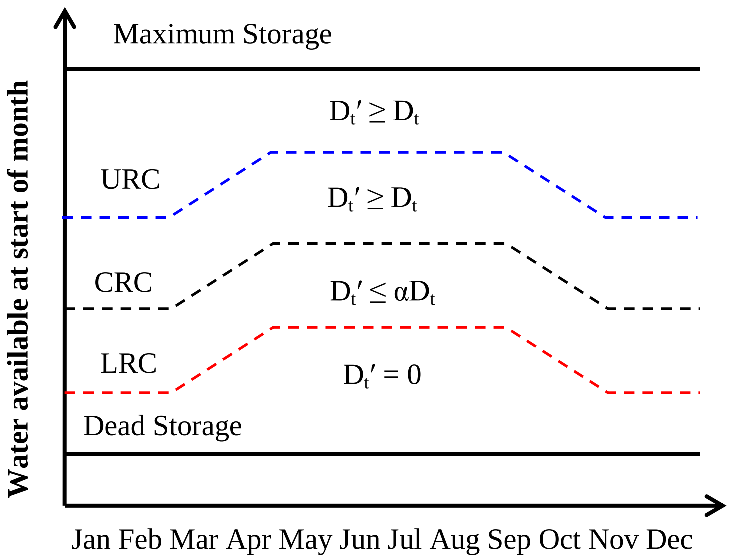
However, despite the numerous strides into resolving the associated issues with SOP-based hedging, it is felt that the practice of hedging when water is already in short supply is inappropriate. For example, the single hedging policy in Figure 2.7 recommends supply cutback when the water is already insufficient. This does not improve reservoir performance or eliminate severe droughts. For hedging to be effective, it should be restricted to regions beyond the target release as shown in Figure 2.7 where there is sufficient water to meet the demand i.e. the region of normal operation in order to save water for future severe droughts (Adeloye et al., 2016). For this reason, the SOP-based approach was not pursued in this study.

2.4.3.2 Zone-based approach

In zone-based hedging, the hedging factors are discrete proportions of release targets for different zonal levels of water availability. A schematic illustration of basic rule curves is shown in Figure 2.8(a), which implements no hedging. Full demand satisfaction is normally attempted whenever the storage level is above the LRC; no release is made if the level falls below LRC. In zone-based hedging a further zone is demarcated using a critical rule curve (CRC) that lies between the URC and LRC, as illustrated in Figure 2.8(b). The CRC thus acts as the trigger for hedging as water rationing starts wherever the water level is below or at the CRC. Determining the CRC and the associated rationing ratio (α) is the main problem of zone-based hedging.



(a)



(b)

Figure 2.8 Schematic illustration of: (a) basic rule curves with no hedging and (b) single stage hedging integrated rule curves

Several research studies (e.g. Eum et al, 2011; Wang and Liu, 2013; Taghian et al, 2013) have applied zone-based hedging integrated with the reservoir rule curve. For example, Tu et al. (2003, 2008) developed the reservoir operating rule with zone-based hedging by optimising both trigger volumes and the rationing factors for a multipurpose, multi-reservoirs system in Southern Taiwan. They first applied a mixed-integer linear programming model for optimising the hedging rules (Tu et al, 2003).

Later, they developed the hedging rule by using a transformation technique to transform the mixed-integer nonlinear constraints to a set of equivalent mixed-integer linear constraints, resulting in a less complex problem (Tu et al, 2008). The objective function used was the modified shortage index (MSI) (see Equation 2.10). The trigger volumes and the rationing factors were determined for each individual 22 years and then the objective function value of the new and current hedging rule were compared. The objective function values of each year of the new hedging rule were significantly lower than those of the current hedging rule.

Taghian et al. (2014) developed hedging rules coupled with rule curves using optimisation with the MSI objective function for the Kosar and Chamshir reservoirs in Iran. The hedging rules improved the operational performance of both reservoirs in terms of vulnerability in comparison to applying the rule curve alone. The time based reliability was, however, reduced due to the number of years with small shortages being increased. However, they did not investigate the effect of hedging on other performance indices such as the resilience or sustainability.

Some studies have investigated the effect of reservoir operation incorporating hedging rules on the climate based operational streamflow forecast. For example, Adeloye et al. (2016) demonstrated that application of hedging can eliminate the impact of water shortage caused by climate change. Their study has evaluated the effect of hedging-integrated reservoir rule curves on the current and climate change perturbed performance of the Pong reservoir in India. The reservoir rule curves i.e. upper and lower rule curves were optimised, then the hedging rule and the rationing ratio were determined by genetic algorithm optimisation. The results demonstrated that the historic vulnerability reduced from 61% (no hedging) to 20% (with hedging). Climate change perturbations decreasing the rainfall by 10% caused the runoff to decrease this in turn caused the vulnerability to worsen to 66% without hedging which was improved to 26% with hedging.

All of the above would suggest that the zone-based approach should be preferred. Its use of rule curves that often form the basis of reservoir operation worldwide is the most attractive feature of the approach. However, much more important is that it does not suffer from the limitation of the SOP-based approach where rationing takes place when the system is already water stressed. Hedging with the zone-based occurs during normal system operation as it should be. Consequently, the zone-based approach will be implemented in this study.

2.5 Reservoir system simulation models

Simulation is the process of modelling the behaviour of an existing or proposed reservoir system. Reservoir simulation is based on the reservoir mass balance equation introduced earlier (see Equation (2.1)). Simulation is used to analyse the effects of proposed management plans: achievement regarding system performance is evaluated based on selected sets of decisions. By definition, the simulation method does not claim that a particular combination of decisions represents the optimal one. The difficulty inherent in this approach is the large number of feasible operation plans (combinations of decisions) that need to be checked. If simulation alone was used, the search for the "best" solution might not only be very tedious, but could also lead to alternatives which are far from the optimal one (Nandalal and Bogardi, 2007). The reservoir system simulation models are conventional simulation models in the sense that no formal mathematical programming (e.g. linear programing, dynamic programing and nonlinear programing) methods are used.

Several software tools utilising simulation have been developed to serve the needs of model users. For example, the model HEC-3 (Reservoir System Analysis for Conservation model) was developed at the USACE (United States Army Corps of Engineers) Hydrologic Engineering Centre (USACE, 1981) for simulating multi-purpose reservoir systems. HEC-3 simulates the operation of a reservoir system for conservation purposes such as water supply, low-flow augmentation, and hydroelectric power. HEC-3 is documented by a user manual (USACE, 1981) and other publications available from the Hydrologic Engineering Centre.

Since then, there have been many modifications to increase its capability such as HEC-5, 'Reservoir System Operation for Flood Control', and HEC-ResSim, 'Reservoir System Simulation', a successor to HEC-5 (USACE, 2003). HEC-5 is probably the most versatile of the available models in the sense of being applicable to a wide range of reservoir operation problems. It has capabilities for detailed simulation of flood control operations. It is also totally generalised for application to any reservoir system as opposed to other models which were developed for a specific river basin. HEC-5 is well documented and has been used for storage reallocation and other operational modifications at existing reservoirs as well as feasibility studies for proposed new projects. HEC-3 and HEC-5 have similar capabilities for simulating conservation operations for water supply diversions and instream flow requirements. However, HEC-3 does not have the comprehensive flood control capabilities of HEC-5.

The study by Madsathan (1984) used HEC-3 for the simulation models using a trial-error method to modify the existing rule curve of the Ubonratana Reservoir in 1984 for water demand of the Nong wai irrigation project. The study showed that the modified rule curve was more suitable than the existing rule curve used by the Electric Generating Authority of Thailand (EGAT), in terms of decreasing total water shortages. The rule curve of the Ubonratana reservoir was studied again by Kangrang et al. (2009). The study used HEC-3 to modify the existing rule curves and policies, which led to improved performance e.g. reducing frequency of water shortage and the average water shortage.

The Water Evaluation and Planning System (WEAP) was developed and is distributed by the Stockholm Environmental Institute Boston Center (SEI, 2011). The model is based on the water balance equation of the reservoir and is designed as a tool for producing water management scenarios, and conducting policy analyses (Wurbs, 2005; Rukuni, 2006). Developers of reservoir systems can use the WEAP model to evaluate its performance as well as plan water allocation. In addition, the model can be used to study and evaluate numerous alternative policies in developing strategies for reservoir management. The WEAP model has been widely used for reservoir system simulation because it is convenient to use easy to comprehend and compatible with other programmes such as Microsoft Excel and GIS (Rukuni, 2006).

For example, WEAP has been used in studies by United Nations agencies, the U.S. Agency for International Development, and other organisations (Wurbs, 2005). Chiamsathit et al. (2014a) used WEAP to develop the existing rule curves of the multi-purpose Ubonratana reservoir in Thailand. The new set of rule curves (URC and LRC) was developed from the existing rule curves using a trial-and-error procedure involving progressively shifting downward its URC and LRC and observing the resulting water shortage relative to the existing rule curves. The new set of rule curves has improved the performance of the reservoir with almost 40% more sustainability than the existing rule curves. The results showed that the time-based reliability of the lowest priority water demand increased from 93% (exiting rule curves) to 98% (new rule curves). In addition, WEAP has been applied to other basins with satisfactory results. For example, it has been applied to Ziz catchment in southeast Morocco to simulate various water allocation scenarios for water management (Salem et al., 2011).

2.6 Optimisation of reservoir system operation

Optimisation models are used to narrow down the search for promising combinations of decision variables. Optimisation eliminates all the undesirable operation plans and proposes policies which are close to the global optimal solution (Nandalal and Bogardi, 2007). However, optimisation usually relies on a very simple representation of a water resources system. Therefore, optimised alternatives may be further refined by applying simulation techniques. The most frequently used optimisation techniques in water resources management can be classified into three major groups: (1) linear programming (LP), (2) dynamic programming (DP), and (3) nonlinear programming (NLP); these techniques are discussed in the next section. This general classification, in addition to simulation models, represents the basic methods used in planning and management of water resources systems (Yeh, 1985). All optimisation models also simulate system performance for alternative decision policies. The objective function and constraint equations incorporated in optimisation models are a representation and, thus, a simulation model of the real system. Optimisation strategies often consist of iterative trial-and-error runs of a simulation model.

2.6.1 Simulation-optimisation models

Since simulation models are limited to predicting the system performance for a given decision policy, optimisation models have a distinct advantage in being able to search through an infinite number of feasible decision policies to find the optimum policy (Ngo et al., 2007). However, simulation models have certain advantages over optimisation models from a practical applications perspective. Simulation models generally permit more detailed and realistic representation of the complex physical and hydrologic characteristics of a reservoir system (Wurbs, 1993). Search algorithms have the advantage of being readily combined with a complex simulation model. The simulation model captures the complexities of the real-world reservoir system operation problem. The search algorithm provides a mechanism to systematise and automate the series of iterative executions of the simulation mode required to find a near optimum decision policy. Simulation-optimisation can be effectively used in combination. An optimisation model may search for an optimum decision policy while activating a simulation model to compute the objective function value for any given set of decision variable values.

Although in general, control rules of existing reservoirs and proposed operating rules are often developed using a simulation model (Kangrang et al., 2008), optimisation is required when searching for the best amongst a number of possible alternatives. In reality, simulation and optimisation modelling approaches are complementary and should be used in all phases of water resources management: planning, design and operation (Faber and Harou, 2007). Wurbs (1993) defined optimisation problems as determining a set of decision variables for maximising or minimising an objective function subject to constraints. Thus, an optimisation model consists of two major components:

- The objective function defines the evaluation criterion in terms of the decision variables
- Constraints are a set of functional equalities or inequalities that control the values of the decision variables

(i) Objective function

The objective function is the driving force in the optimisation models. In general, the objective function depends on the purpose of the reservoir. For example, if the main purpose of a reservoir is to generate hydropower, then the objective function is the maximising hydropower generation or the total net benefit associated with generating hydropower (Jaafar, 2014; Regularwar et al., 2010). If the main purpose of a reservoir is water supply, then the objective function can be maximising water supply (Ndiritu, 2005). If the main purpose of the reservoir is for flood control, the objective function is based on minimising flood peak or minimising flood frequency (Connaughton, 2014).

For reducing drought damages, the objective function is defined in terms of shortage minimisation such as total water shortage as defined in Equation (2.25), the sum squares of the period shortages (SS) as defined in Equation (2.26) and the modified shortage index (MSI) as defined in Equation (2.27).

(1) Minimising the total water shortages:

$$\text{Minimise } \sum_{t=1}^{N}(D_t - D'_t), \forall D'_t \leq D_t \tag{2.25}$$

where D_t is water demand during period which is known, t; D'_t is water released during period, *t, which is a decision variable* and N is total number of time periods. This objective function attempts to minimise the total deficit, thus the total shortages of the whole system can be reduced.

(2) Minimising the sum squares of the period shortages (SS) (Chiamsathit et al., 2014b):

$$\text{Minimise } \sum_{t=1}^{N}(D_t - D'_t)^2, \forall D'_t \leq D_t \tag{2.26}$$

This objective attempts to minimise the volume of single-period shortage by using the quadratic objective function. Using the squared deficits in Equation (2.26) attempts to minimise the large single period shortages compared to Equation (2.25). For example, there are two different solutions (1) 5 times periods each with 2 units of water shortages; (2) 2 time periods each with 5 units of water shortages. The objective function value is 10 units for both solutions when using Equation (2.25), but it is 20 and 50 units for solution 1 and 2, respectively, when using Equation (2.26). The algorithm using Equation (2.26), then converges to solution 1, because of the minimum objective function value. The advantage of Equation (2.26) is that the individual deficit magnitudes are squared in order to penalise the large deficit and convert them into smaller deficit.

(3) Minimising rule the modified shortage index (MSI) (Hsu and Cheng 2002) i.e.:

$$MSI = \frac{100}{N}\sum_{t=1}^{N}\left(\frac{TS_t}{D_t}\right)^2 \qquad (2.27)$$

where TS_t total shortage in the t^{th} period (month); D_t is total demand in the t^{th} period; N is total number of time periods. This index implies that the effect of a deficit is proportional to the square of the deficit ratio.

(ii) Constraints

The constraints restrict the solution within a limited area, which is known as the feasible region (Jain and Singh, 2003). Constraints of a reservoir operation problem typically include reservoir capacity and other physical reservoir characteristics, water requirements for various purposes, water balance, and hydropower generation limitations (Yeh, 1985).

For example, the constraints are:

$$S_t \leq Ka$$

$$S_t \geq 0$$

$$S_{t+1} = S_t + Q_t - D_t - E_t - Y_t$$

$$D_t = D_{p,t} + D_{d,t} + D_{i,t}$$

where S_t and S_{t+1} are the volume of storage at the beginning and end of the interval, respectively, Ka is the storage capacity of the reservoir, Q_t is the inflow to the storage during the interval, D_t is the total water demands during the interval which consists of public ($D_{p,t}$), downstream ($D_{d,t}$), and irrigation demands ($D_{i,t}$), Y_t is the spilling during the interval, E_t is net evaluation.

Many complex simulation models also contain optimisation algorithms to perform certain functions. For example, HEC-5 contains an iterative search algorithm to determine flood control releases for each time interval during the simulation, following user specified operating rules. HEC-3 and HEC-5 contain firm yield requirement which empties the storage capacity of a single reservoir or multiple reservoir system. There are many examples of optimisation applications in the literatures. For example, Faber and Harou (2007) applied simulation and optimisation models by using HEC-ResPRM (i.e. the integration of HEC-PRM ("Prescriptive Reservoir Model") and HEC-ResSim) for evaluation and improve the operation of the Mississippi Headwaters system. HEC-ResPRM (USACE, 2003) is a generalised software tool for creating linear deterministic optimisation models of multi-purpose reservoir systems and its details were also described in their paper. Ngo et al. (2008) optimised the rule curves of the Hoa Binh in Vietnam, a multi-purpose reservoir, using optimisation algorithm with MIKE 11 (a model system for rivers and channels) to increase hydropower production.

2.6.2 Solution Algorithms

Available solution schemes of constrained optimisation problems are varied and are largely dictated by the form of the objective and constraint equations. In the past, mathematical programming techniques have been applied in water resources problems including linear programming (LP), dynamic programming (DP), and nonlinear programming (NLP) (Mays and Tung, 1992; Tingsanchali and Boonyasirikul, 2006; Ngo et al., 2007). An extensive review of these optimisation techniques is also available in Wurbs (1993). Recently, researchers have developed computational optimisation methods based on biology such as genetic algorithm (GA), particle swarm optimisation (PSO), ant colony (ACO) and honey-bee mating optimisation (HBMO) (Kumar and Reddy, 2007; Dariane and Moradi, 2008; Moradi and Dariane, 2009; Guo et al., 2013). These optimisation approaches search from a population of points, so there is a greater possibility of arriving at the global optimum. For example, GA is a guided random search optimisation algorithm inspired by biological selection and evolution. While this thesis has adopted the GA as the main solver of the reservoir optimisation problem as discussed in 2.6.3 (apart from limited NLP solution from comparison sake), a brief review of other common formulations and solution schemes is first presented.

2.6.2.1 Linear programming (LP)

LP has been one of the most popular optimisation techniques and widely applied in water resource management due to its simplicity in problem formulation (Mays and

Tung, 1992; Wurbs, 1993; Devi et al., 2005; Nandalal and Bogardi 2013). As the name implies, LP relies on a linear objective function and a set of constraints which can be equality or inequality.

Linear programming has the advantage of having low dimensionality compared to other optimisation schemes, which is why large-scale problems can be solved readily using LP. Other advantages of LP for reservoir management and operations are documented by Barros et al. (2003). In particular, their study compared the optimisation results obtained from the linearised and NLP models to develop the management and operations of the Brazilian hydropower system and it was found that LP model produced excellent results with fast convergence.

Most reservoir optimisation models, however, consist of nonlinearity, time-dependent variables, multi-objective criteria, discontinuity, and several constraints. Therefore, it is difficult to use LP in such cases without significant simplifying assumptions and approximations e.g. involving piecewise linearisation of the objective function. Nonetheless, LP remains the most widely used optimising formulation for water resource management problems. For example, Devi et al. (2005) developed LP to maximise annual benefits from irrigation and hydropower according to the water shares among riparian cobasin states, i.e. Bihar, Orissa and West Bengal in the Subernarekha River, a large river basin in India. Ziaei et al. (2012) used LP for optimising the rule curves for the Zayandeh Rud reservoir in Iran under the objective function of maximising the total reservoir release. The optimal rule curves produced an increase of 6.1% of the water supply and increased 19% time-based reliability.

2.6.2.2 Dynamic programming (DP)

DP is another well-known optimisation model to define the optimal operation rules of a reservoir system (Nandalal and Bogardi, 2013). Originally, according to Bellman (1957), DP was used to solve multi-decision or multiple-period reservoir operations that contain many decision variables by decomposing them into simpler minor problems or subproblems, each containing only one or a few variables (Mays and Tung, 1992; Nandalal and Bogardi 2007; 2013). Each sub-problem (stage) is optimised, and the optimal solution is then transferred to the next sub-problem using the stage equations.

Dynamic programming is so called multi-stage programming, normally started from the first stage and then processing sequentially to the last stage, in which case the solution method is called forward recursion. Instead of starting at the first stage and working forwards, for some problems, the evaluation determines the optimum by an opposite procedure called backward recursion. The characteristic of a DP formulation is presented by Jain and Singh (2003).

A significant feature of DP is that the objective function can have nonlinearities, but constraints must be linear in the decision variables (Jain and Singh, 2003). Thus, this property is very useful because objective functions in many problems cannot be realistically linearised. DP is widely used for optimising reservoir operations because of its benefit of fast convergence (Chuanzhe et al., 2011). For example, Kangrang and Chaleeraktrakoon (2007) applied a DP approach to find the optimal rule curves of multi-purpose Bhumibol and Sirikit reservoir systems in Chao Phraya river basin, Thailand under the objective function of minimising water shortage. However, this study proposed only the optimised upper and lower rule curves without the performance evaluation.

In general, the advantage of LP over DP is that standard, well defined, easy to understand algorithms are readily available in the form of generalised computer codes; furthermore, there is no dimensionality problem (Jain and Singh, 2003; Salami and Sule, 2012). Kangrang and Chaleeraktrakoon (2007) found that the technique has often encountered a dimensionality problem and that the discrete algorithms are not suitable because the state variables (upper and lower water levels) of the curve searching rule are continuous. DP is also more difficult to learn and understand than LP, especially in multi-dimensional problems. DP separates objective functions and decision variables at each stage that would be evaluated for all discrete combinations of state variables, thereby creating numerous problems for computer capabilities and consuming time.

2.6.2.3 Nonlinear programming (NLP)

NLP is an optimisation approach in which the objective function and/or at least one constraint are nonlinear functions of the decision variables (Jain and Singh, 2003). Nonlinear functions are common in modelling reservoir operation. For example, objective functions of benefits or costs are normally expressed as a nonlinear function of storage and discharge. In general, reservoir water surface area-storage relationship required for evaporation computations are a nonlinear constraint. NLP provides a more general mathematical formulation than LP, but the mathematics involved are much more complicated. NLP can model the nonlinearity more accurately than linear programming and dynamic programming (Yousif, 1999). Therefore, NLP is widely applied for optimising hydropower systems (Jothiprakash and Arunkumar, 2014).

For example, Barros et al. (2003) applied a monthly NLP optimisation model to the Brazilian hydropower system, one of the largest in the world. The results of the study show that the NLP model meets the demand and produces more energy by maximising storage and by minimising spill. Therefore, the NLP model is beneficial for guiding real-time operation. Jothiprakash and Arunkumar (2014) developed an NLP model for maximising hydropower production and solved three different dependable inflow scenarios (wet, normal, and dry) under various operating policies for the Koyna reservoir, India.

The limitations of NLP have been reviewed by Yousif (1999) and include the complexity of the optimisation problem, the large order of dimensionality, the low convergence rate to solve a problem, and the large computer memory required. Search methods of NLP are more complex to implement than those of LP and DP and sometimes become trapped in local optima (McMahon and Adeloye, 2005; Li et al., 1998; Hossain and El-Shafie, 2013). Presently, general purpose software packages such as LINGO and MINOS are available for solving large-scale nonlinear optimisation problems. The software packages are commonly used for solving complex problems including reservoir operation for hydropower generation.

2.6.2.4 Other newer schemes

As indicated earlier, some examples of newer schemes for optimisation based on biology such as particle swarm optimisation (PSO), ant-colony (ACO) and honey-bees mating optimisation (HBMO). PSO is a swarm intelligence method proposed by Eberhart and Kennedy (1995), inspired by the social behaviour of bird flocking as they rush towards the food or their habitats, and it consists of a population (swarm) and members of population (particles). PSO is a population-based search algorithm and find the optimal solution like GA, but there is no operation of natural evaluation is applied to select a new generation of candidate solution. Thus, PSO relies on the exchange of information in the discoveries and experiences between members of a population to change its position and move toward to the better position. It was found that PSO has a faster rate of convergence compared to GA (Salman et al., 2002), but it has difficulty in obtaining the optimal solutions in complex functions (Kumar and Reddy, 2007).

ACO was proposed by Dorigo (1992) for solving optimisation problems and is inspired by the foraging behaviour of real ants in finding the shortest path from their nest to food sources. Ants search for food in the area around their nest in a random way. Once the food source is met by any one of them, it evaluates and transfers some food back to the nest by depositing a strong pheromone on the ground in order to guide other ants to the food source.

Honey-bee optimisation was inspired by several complicated behaviours such as mating, breading and foraging. One famous honey-bee optimisation is honey-bees mating optimisation (HBMO) which is inspired by the process of mating in real honey-bee (Abbass 2001; Haddad et al., 2004). The algorithm starts with the mating flight whereby a drone is randomly selected for the creation of new broods. A brood is constructed by copying some of the drone’s genes into the brood genotype and completing the rest of the genes from the queen’s genome. The fitness is then determined by evaluating the value of the objective function of the brood genotype. The best brood replaces the worst queen until there is no brood that is better than any of the queens. HBMO is well described by Afshar et al. (2007).

Recently, application of these new optimisation schemes for water resources management has been studied. Haddad et al. (2006) presented an optimisation algorithm based on honey-bee optimisation. HBMO was applied to a single reservoir operation of the Dez reservoir in Iran under the objective function of minimising the total squared deviation of releases from the target demands. The results over 10 runs showed that the best result of the HBMO algorithm was 3% higher than the global optimum. Under the same reservoir and objective function of Haddad et al. (2006), the ACO was applied for optimising the reservoir operation by Jalali et al. (2006). The best fitness value of ACO over 10 runs was 1.3% higher than the global optimum. Later, the optimisation of the Dez reservoir was studied by Moradi and Dariane (2009) using PSO under the objective function of minimisation of sum of deficit square. The objective function results over five runs in PSO were compared to ACO and it was found that the best fitness value obtained by PSO was 3.5% higher than that in ACO and 7% higher than the global optimum: i.e. ACO performed better than PSO.

2.6.3 Genetic algorithm (GA) for optimisation

Genetic algorithms (GA), invented by Holland (1975), have emerged as practical, robust optimisation and search methods. Goldberg (1989) described the genetic algorithms (GA) as a stochastic numerical search method based on the principles of natural genetics in selection and evolution. They combine the concept of the survival of the fittest with genetic operators extracted from nature to form a robust search mechanism. Good descriptions of GAs and subsequent developments can be found in Goldberg (1989) and Forrest (1993). GA has been widely applied in many fields such as science, business, and engineering (Wang, 1991; Chang et al., 2005). GA is often preferred over other search techniques because of its ability to search for the solution from a population of points (rather than a single point), and its use of the objective function information itself rather that the derivatives of the function. Further details about the GA are given in section 2.6.1, but for now some examples of its application in reservoir management problems are given.

Many researchers have developed the optimisation of reservoir operation based on the GA approach and determined that this approach increased the efficiency of water supply performance (Chang et al., 2005; Ahmed and Sarma, 2005; Chang et al., 2010). The GA approach is suitable for the complex problem of optimising hedging to establish the timing and amount of rationing (Adeloye et al., 2016; Chiamsathit et al., 2014b; Shiau, 2009). GA has also been applied to reservoir operation for developing optimal rule curves and operating policies (Reddy and Kumar, 2006; Kangrang et al., 2008; Hormwichain et al., 2009; Chang et al., 2010; Ngoc et al., 2013; Taghian et al., 2013). For example, Kangrang and Chaleeraktrakoon (2007) developed the optimal rule curves for the Bhumibol and Sirikit reservoir (multi-reservoir system) in Thailand using a GA technique combined with the simulation model HEC-5 that was able to reduce the effect of the correlations on the water shortage situation. Reddy and Kumar (2006) applied a multi-objective genetic algorithm to a multi-purpose reservoir, which suggests that GA has potential in optimising operating rules with conflicting objectives.

GA requires encoding schemes that transform the decision variables into chromosomes. In general, there are two different coding schemes to represent an optimal solution-binary coding using binary bit strings and real coding using a string of real numbers (Chang et al., 2005). It has been found that real-coded GA has advantages over binary-coded GA (Bessaou and Siarry, 2001). Chang and Chen (1998) determined that the three advantages are precision, efficiency, and flexibility. Jian-xia et al. (2005) also found that the optimisation of reservoir operation policies using real-coded GA was significantly faster than that using binary-coded GA and could produce better results. Chang et al (2005) demonstrated that the optimisation of operating rule curves for the Shih-Men reservoir in Taiwan using GA had better performance in terms of water supply than the current operating rule curves, and real-coded GA was found to be more efficient than binary-coded GA. Consequently, real-coded GA is attractive to use and should be adopted.

The comparative study of Azamathulla et al. (2008) between GA and LP for real-time reservoir operation was implemented for the Chiller reservoir system in India. The study considered the soil moisture status and the reservoir storage as the state variables and the applied irrigation depths as the decision variables to obtain an optimal operating and crop water allocation policy. The yield of crop is affected by water deficits and the evapotranspiration rate. Hence, the objective function is to maximise the evapotranspiration rate in order to minimise the deficits in the yield. The GA model gave better yields from optimum allocation of the available water when compared to LP model.

2.6.3.1 Basis of standard genetic algorithms (SGA) for optimisation

In GA, the solution set is represented by a population of strings, which comprises a number of blocks each representing the individual decision variables of the problem (Jinchai and Chittaladakorn, 2012). Strings are processed and combined according to their fitness (objective function value evaluated using the components in the string) in order to generate new strings that have the best features of two parent strings. Strings with the best fitness have the greatest chance to produce future generations, similar to the process of natural selection (Gumustekin et al., 2014). The objective or fitness function is a key to the use of GA because it is the mathematical expression describing the integrity of the solution. Moreover, the most time-consuming part in GA optimisation is often the evaluation of the objective function (Raff et al., 2012).

As seen in Figure 2.9, genetic operations - selection, crossover and mutation (Michalewicz, 1992) - are carried out to create a new generation of solution population. This new generation undergoes similar "fittest" solution identification, and the whole process is repeated over several generations until the stopping criterion is met (e.g. no improvement in the fitness value or reaching a given number of generation), at which point the optimum solution is said to have been reached, so called the standard SG (SGA). Because the GA is initialised with random numbers which are unlikely to be the same over repeated trials or sets, the algorithm in Figure 2.9 is normally repeated several times, and either an average solution or the best among the iterations is taken as the optimal solution. Factors that affect the convergence include the number of generations, the population size and the number of repetitions. Detailed descriptions of their operations and other key parameters of the SGA are presented next.

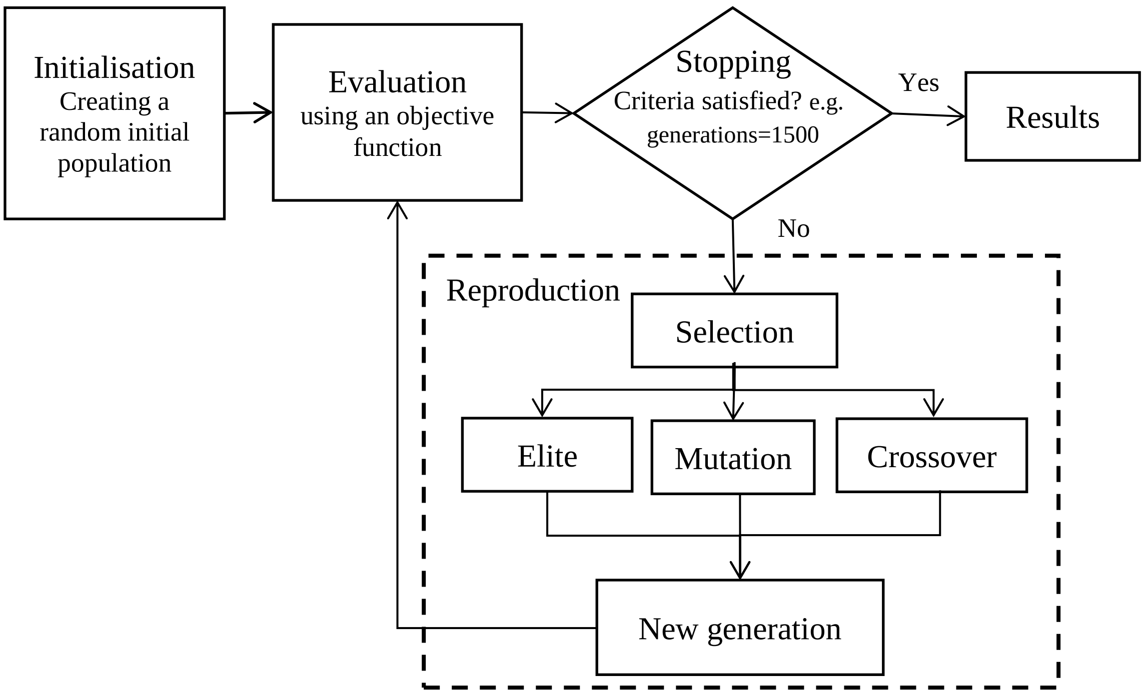


Figure 2.9: Simple Genetic Algorithm Flowchart

(i) Initialisation

The GA process begins with the random generation of an initial population of feasible solutions which is a set of solutions or chromosomes having randomly generated decision-variable values within the boundary.

For example, a chromosome (C_j) representing search space for optimising monthly rule curves is:

$$C_j = \{URC_1, URC_2, \ldots, URC_{12}, LRC_1, LRC_2, \ldots, LRC_{12}\} \tag{2.28}$$

Each gene within the chromosome represents monthly rule curve and can take up any value between the upper and lower bounds. The decision variables are URC and LRC which are upper and lower rule curve, respectively. In real-coded GA, randomly generated numbers within the upper and lower limits of the bounds generate chromosomes of the population. The number of chromosome generated depends on the population size. The performance of a GA is influenced by the diversity of the initial population, which involves population size and initial range. The key parameters of the initialisation are presented as below.

(1) The population size

Population size (number of chromosomes) specifies the number of solutions in each generation. With a large population size, the algorithm could search more points and thereby obtain a better result (Purohit et al., 2013). However, an excessively small population could guide the algorithm to poor solutions, while an excessively large population could significantly increase the computational time in finding a solution (Alolfe et al., 2007; Roeva et al., 2013). Consequently, many researchers have attempted to determine optimal population size (Gotshall and Rylander, 2002; Haupt and Haupt, 2000; Rajakumar and George, 2013). However, Gotshall and Rylander (2002) found that increasing the population size increases the accuracy of GA and also causes the increasing generations to converge. Roeva et al. (2013) found that the optimal population size is 100 solutions and that increasing the size does not improve the objective function values.

(2) Initial range

Initial range specifies the range of the initial population, which is directly linked to the diversity. If the diversity is too high or too low, the genetic algorithm might not perform well. A too narrow initial range will cause the algorithm to be trapped in a local minimum due to the initial range restriction. Conversely, if the range is too wide, the algorithm will require more generations to find a better solution (Purohit et al., 2013). If the initial supply of solution space is not of the proper size or quality, it will be difficult for a GA to find a good solution; a better initial population leads to a better solution (Diaz-Gomez and Hougen, 2007). It was recommended that the middle of the initial range should be close to where the minimal point for a function lies (MathWorks, 2004). For example, if the minimal point for a function is close to zero, the initial range should be set at [-1; 1]. The initial range only restricts the range of the points in the initial population, but the individuals in all generations are restricted by the constraint bounds. The constraint boundary specifies the lower and upper bounds on the decision variables. If the optimisation problem has n decision variables, the lower and upper bounds are vector of length n. Therefore, it has to ensure the feasible region (where the global optimum could be located), is within the constraint boundary.

(ii) Evaluation of fitness values

As stated earlier, the algorithm begins by creating a random initial population. After the generation of the initial population, which consists of chromosomes containing decision variables (rule curves), then the next step, the fitness value for each chromosome, is calculated by using the objective function; this process is called evaluation. The fitness assigned to each gene has direct influence on the eligibility for each chromosome to be selected in the next generation. Thus, this process involves determining values for a set of decision variables that will minimise or maximise an objective function subject to a set of constraints.

(iii) Reproduction

Reproduction is applied to generate new population. The reproduction process consists of selection, crossover and mutation and carries out the selected chromosomes to create a new set of chromosomes that makes the population for the next generation. A chromosome with the highest fitness has a greater chance of contributing to the next generation, as in the process of natural selection. After the mutation process finishes, then we have one iteration or one generation of the genetic algorithm. Next, the objective function is evaluated after one generation is produced. All steps are repeated except generating the initial population until the best solution is obtained. The reproduction process (i.e. selection, elite count, crossover and mutation) is described as below.

a. Selection

The selection operation helps to identify the strings to be included in the reproduction process for developing the next generation of strings. The fitter solution has the greater chance of survival than the weaker one. Selection approaches specify how the GA chooses parents for the next generation. There are a number of approaches for selection, all of which determine the probability of selection as a function of fitness. The common approaches are roulette-wheel, stochastic uniform, and tournament, described as follow.

(1) Roulette-Wheel selection

Roulette-wheel selection approach chooses parents by simulating a roulette wheel, in which the area of each segment is proportional to the individual's expectation, as seen in Figure 2.10. The algorithm uses a random number to select one of the sections with a probability equal to its area. The probability of the maximisation is expressed as Equation 2.12. Fitter solutions will represent a larger range in the cumulative probability values and therefore have a better chance of being selected in the reproduction process. On the other hand, weaker solutions will represent a smaller range in the cumulative probability values and have a smaller chance of being selected in the reproduction process (Mathew, 2005). The functioning of the roulette wheel algorithm is described below:

Step1: Calculate the sum of all chromosomes fitness in the population, as seen in Table 2.1.

Step2: Generate random numbers from the given population interval.

Step3: Go through the entire population and sum the fitness. When this sum is more than a fitness criteria value, stop and return this chromosome.

The probability of the maximisation for selecting i^{th} solution is:

$$P_i,\% = \frac{F_i}{\sum_{i=1}^{n} F_i} \times 100 \tag{2.29}$$

Where n is the population size, F_i is fitness value of i^{th} solution. The following table lists a sample of 5 solutions (the tested population of 200 would be difficult to illustrate). Table 2.1 and Figure 2.10 show an example of the maximisation by using roulette wheel selection. The solution no.5 has the highest fitness value, then it will have the highest probability of selection (39%). Conversely, the solution no.2 is the weakest solution due to the lowest fitness value, and has the lowest probability of selection (5%).

Table 2.1 Example of the roulette wheel selection of a single solution

Solution No.	Fitness f(x)	P_i
1	3,400	13
2	1,200	5
3	4,800	19
4	6,300	24
5	10,200	39
Total	25,900	100

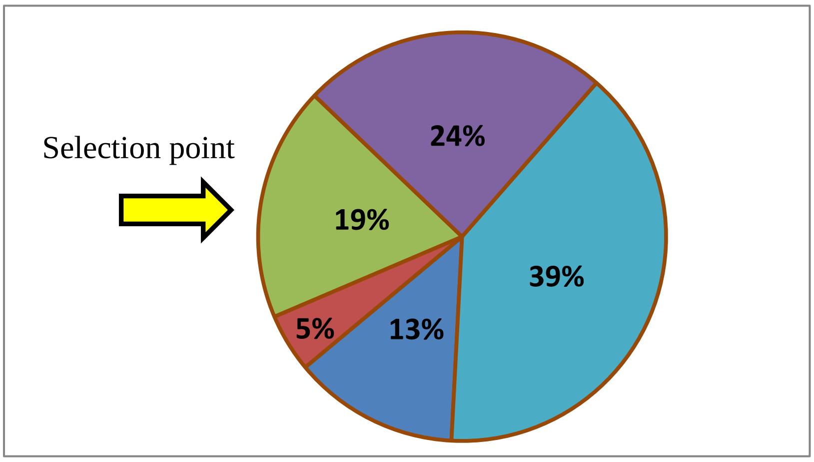


Figure 2.10 Roulette wheel approach based on each solution’s relative fitness

(2) Stochastic uniform selection

Stochastic uniform selection approach lays out a line in which each parent corresponds to a section of the line of the length proportional to its scaled value. The algorithm moves along the line in steps of equal size, one step for each parent. At each step, the algorithm allocates a parent from the section it lands on (MathWorks, 2004). Figure 2.11 illustrates the stochastic uniform; the individuals are mapped to contiguous segment of a line, such that each individual's segment is equal in size to its fitness exactly as in roulette-wheel selection. Here equally spaced pointers are placed over the line as many as there are individuals to be selected. The number of individuals (H) is selected, then the distance between the pointers is $\frac{1}{H}$ and the position of the first pointer is given by a randomly generated number in the range $[0, \frac{1}{H}]$.

For example, two individuals will be selected from a set of solutions in Table 2.1, the distance between the pointers is $\frac{1}{2} = 0.5$. Figure 2.11 shows the selection for the example in the stochastic uniform. As, seen in Figure 2.11, after selection, the mating population consists of the individuals: the solution number 5 and 3.

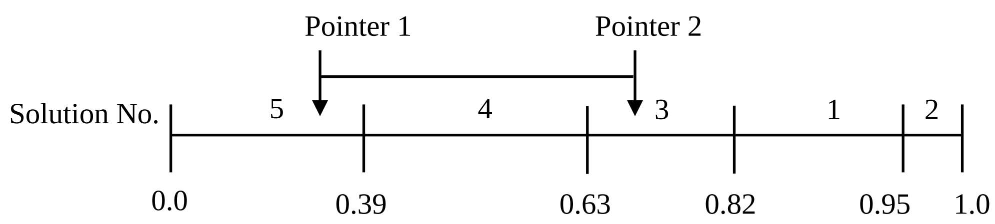


Figure 2.11 An example of the stochastic uniform selection

(3) Tournament selection

Tournament selection was inspired from the natural process of individuals competing with each other in order to mate. The chromosomes in the population are selected for competition, usually randomly, with the victor increasing its expected incidence in the mating pool. In this approach, a number of individuals is chosen randomly from the population and the best individual from this group is selected as parent. Initially the entire population is in the tournament. A pair of solutions is selected at random to complete against each other with only the winner of the competition processing to the next level of tournament (i.e. the better fitness is expected to appeal in the mating pool). Figure 2.12 illustrates tournament competition between solutions, several tournaments are held between the solutions of current generation. The process is repeated as often as desired (usually until the mating pool is filled).

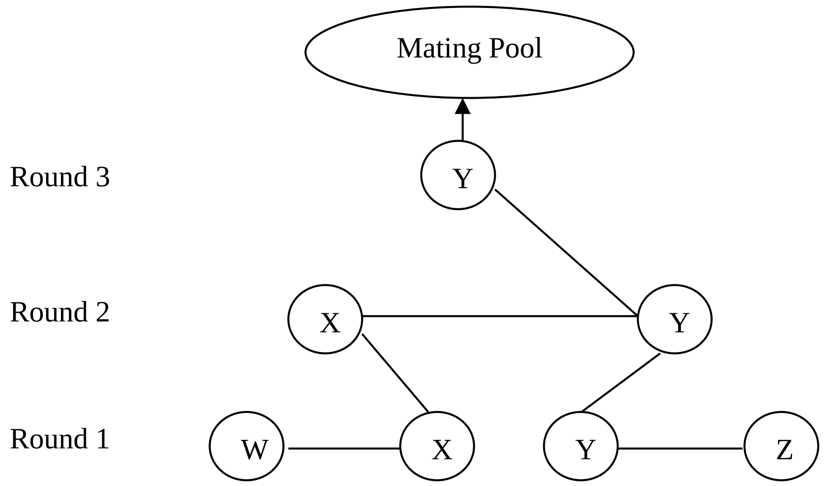


Figure 2.12 An example of tournament selection

b. Elite count

Elite count specifies the number of strings (called elite children) with the best fitness values in the current generation that are guaranteed to survive to the next generation. A high value of elite count causes the fittest individuals to dominate the population, which can make the search less effective (MathWorks, 2004). The elite children should have a low value (1 or 2) depending on the population size (Purohit et al., 2013); high population size may use higher elite child. The default value recommended in Matlab software is 5% of population size (MathWorks, 2004).

c. Crossover

In crossover operation or recombination, the crossover operator generates new points (children) based on selected points (parents) from the selection process that were previously sampled from the search space (Melo et al., 2007). Crossover approaches specify how the genetic algorithm combines two or more solutions to form a better solution (a new child) for the next generation with a probability of crossover rate (Abdoun and Abouchabaka, 2011). Crossover rate is the fraction of strings in the next generation other than elite children that are produced by crossover (those remaining are generated by mutation). When individuals are not subjected to crossover, they remain unmodified. For example, a crossover rate of 0.9 means that 90% of the population is undergoing the crossover operation. A crossover rate of 1 indicates that all children other than elite children are crossover children. If crossover fraction is 0, all children are mutated (Purohit et al., 2013).

Too high crossover rates may ignore solutions with higher fitness while too low crossover rates may truncate the search due to low rate of exploration (Chiroma et al., 2013). Typical values of crossover rate are in the range of 0.5 to 1.0 (Lin et al., 2003), but crossover rate commonly used lies between 0.6 and 0.9 (Bandyopadhyay and Saha, 2013; Sakawa, 2002). The default value of crossover rate recommended in Matlab is 0.8 (MathWorks, 2004). There are various approaches to crossover—one-point crossover, two-point crossover, scattered crossover, arithmetic crossover, and heuristic crossover, these are illustrated in Table 2.2.

(1) One-point crossover

In one-point crossover, both parent solutions are divided by one point, and then mixing one part of the two parents is exchanged to form the children.

(2) Two-point crossover

In two-point crossover is very similar to single point crossover except that two cut-points are randomly generated instead of one.

(3) Scattered crossover

Scattered crossover creates a random binary vector as the same length as parents' solutions. Data of the first parent chromosome and second parent chromosome are randomly copied. The first child is produced by combining parts of solutions (genes) where the vector is a 1 from the first parent, and the vector is a 0 from the second parent, and the opposite value is assigned to the second child (MathWorks, 2004).

Table 2.2 Various types of crossover function

Type of Crossover	Parents	Children
One point	1st: x_1 x_2 x_3 x_4 x_5 2nd: y_1 y_2 y_3 y_4 y_5	1st: x_1 x_2 y_3 y_4 y_5 2nd: y_1 y_2 x_3 x_4 x_5
Two point	1st: x_1 x_2 x_3 x_4 x_5 2nd: y_1 y_2 y_3 y_4 y_5	1st: x_1 y_2 y_3 x_4 x_5 2nd: y_1 x_2 x_3 y_4 y_5
Scattered	1st: x_1 x_2 x_3 x_4 x_5 2nd: y_1 y_2 y_3 y_4 y_5 1 0 1 1 0 Random crossover vector	1st: x_1 y_2 x_3 x_4 y_5 2nd: y_1 x_2 y_3 y_4 x_5
Arithmetic	1st: x_1 x_2 x_3 x_4 x_5 2nd: y_1 y_2 y_3 y_4 y_5	1st: x'_1 x'_2 x'_3 x'_4 x'_5 2nd: y'_1 y'_2 y'_3 y'_4 y'_5
Heuristic	1st: x_1 x_2 x_3 x_4 x_5 2nd: y_1 y_2 y_3 y_4 y_5	1st: x'_1 x'_2 x'_3 x'_4 x'_5 2nd: x_1 x_2 x_3 x_4 x_5

(4) Arithmetic crossover

Arithmetic crossover produces two new children that are convex combinations of the parents. If the solutions, $\overline{X} = (x_1, x_2, \ldots x_n)$ and $\overline{Y} = (y_1, y_2, \ldots y_n)$ are selected for the parent, where n= numbers of gene, the children are defined as:

$$\overline{X}' = r\overline{X} + (1-r)\overline{Y} \text{ ; (first child)} \tag{2.30}$$

$$\overline{Y}' = (1-r)\overline{X} + r\overline{Y} \text{ ; (second child)} \tag{2.31}$$

Where r is random variables between 0 and 1 that can ensure the gene of new children (x'_i and y'_i) are within the constraint boundary.

(5) Heuristic crossover

Heuristic crossover combines two chromosomes and produces the first child and the second child copies the fitter parent. If the fitness of parent $\overline{X}$ is better than $\overline{Y}$, thus the children are defined as:

$$\overline{X}' = \overline{X} + r(\overline{X} - \overline{Y}) \text{; (first child)} \tag{2.32}$$

$$\overline{Y}' = \overline{X} \text{; (second child)} \tag{2.33}$$

Modupe et al. (2013) stated that the most suitable GA functions of stochastic uniform selection, and scattered crossover, generated the best fitness value for energy consumption. While Bocko et al. (2011) demonstrated that the best result of the experimental data was obtained using stochastic uniform selection and scattered crossover, tournament selection produced the worst results. The comparative study of Alabsi and Naoum (2012) investigated that each selection process (i.e. roulette wheel and tournament), the scattered crossover gave better results than one- and two-point crossover. Additionally, roulette wheel selection with one-point crossover gave better results than tournament selection with one-point crossover. Although several studies have attempted to determine the best setting for the functions of reproduction, no universal rules have yet been established (Chang et al., 2005; Bocko et al., 2011; Diaz-Gomez and Hougen, 2007).

d. Mutation

Mutation introduces genetic diversity into the population by randomly modifying the solutions and enables the GA to search a broader space, as seen in Figure 2.13 (Rani et al., 2012). Crossover is referred to as the exploitation operator, and the mutation is the exploration operator (Malhotra et al., 2011). Crossover operation cannot generate genetic diversity from their parents. On the other hand, an alternate operator or mutation can search new areas in contrast to the crossover and increase population variability in order to increase the probability of finding the global optimum (Patil and Bhende, 2014). The mutation operator is used to change some elements of selected individuals in the population with a probability of mutation, which provides genetic diversity to create mutated children (MathWorks, 2004).

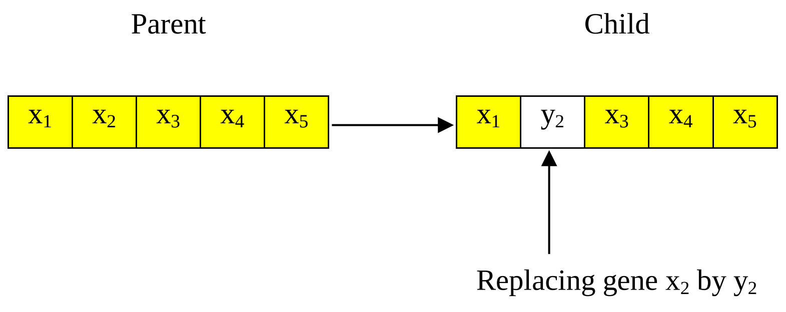


Figure 2.13 An example of mutation

The number of chromosomes that have mutations in a population is determined by the mutation rate parameter. The mutation process is done by replacing the gene at a random position with a new value. There are various approaches to mutation such as uniform, Gaussian, and adaptive feasible.

(1) Uniform mutation

Uniform mutation is a two-step process. First, the algorithm selects a fraction of vector entries of a string for mutation, where each entry has the same probability as the mutation rate of being mutated. The default value of rate recommended in Matlab is 0.01 (MathWorks, 2004) which is widely used in GA (Briand et al., 2013). Next, the algorithm replaces the value of the chosen gene with a uniform random value between the user-specified upper and lower bounds for that gene.

(2) Gaussian mutation

Gaussian mutation consists of adding a random value from a Gaussian distribution with mean zero to each element of an individual's vector to create a new child. This approach is commonly used for unconstrained problems because there is no constraint boundary.

(3) Adaptive feasible mutation

Adaptive feasible mutation randomly generates directions that are adaptive with respect to the last successful or unsuccessful generation.

An excessively high mutation rate increases the probability of searching more areas in the search space; however, it also increases the probability of destroying potentially good solutions as more elements within the solutions are modified (MacFarlane et al., 2010). Conversely, an excessively small mutation rate cannot avoid premature convergence (falling into local optima instead of global optimum) (Falaghi and Singh, 2010). For example, if the population size is 200, string length is 10, and default mutation rate is 0.05, then 10-bit positions (i.e., 200 × 10 × 0.05) will mutate in the whole population. Typical values of mutation rates are in the range 0.001 to 0.01 (Lin et al., 2003; Sakawa, 2002), and the rate of mutation probability is always lower than crossover probability (Chiroma et al., 2013).

Low probabilities of mutation are commonly used in GA (Lin et al., 2003; Reddy and Kumar, 2006; Rani et al., 2012). For example, Reddy and Kumar (2006) chose the crossover and mutation rates of 0.9 and 0.03, respectively, for optimal reservoir operation using multi-objective genetic algorithm. The investigation of Haupt and Haupt (2000) demonstrated that a small population size and relatively large mutation rate is much better than a large population size and low mutation rate. Their experiment suggested that the best mutation rate for GA lies between 5% and 20% of the population size. Suiadee and Tingsanchali (2007) used crossover and mutation rates of 0.75 and 1, respectively, for optimal rule curves of a reservoir in Thailand. Zahraie and Hosseini (2010) specified a crossover rate of 0.7 for development of reservoir operation policies. Rani et al. (2012) used crossover and mutation rates of 0.6 and 0.05, respectively, for their applications to water resources systems.

2.6.3.2 The challenges of SGA

Attaining the global minimum (or maximum) of a function is a challenge for most optimisation solution algorithms including the SGA. In general, the SGA often fails to search adequately for the global optimum, leaving it trapped in local optimum, and is time consuming, especially when the search space is not in an optimal space. This is because the search space is defined by a finite number of points located within the constraint boundary. An excessively wide boundary will increase the computational time, and an excessively narrow boundary may lead to the solution missing the global optimum (Purohit et al., 2013). Thus, while a narrow boundary may be attractive in terms of computational time, due diligence is required to ensure that the boundary domain for the search does indeed contain the true optimal solution.

As stated earlier, to ensure the best solution is obtained, the algorithm is normally repeated several times. There is no rule for the optimal number of iterations. Too many iterations waste time and consume excessive computer memory, and too few iterations may not ensure the validity of the global optimum. For example, Maaranen (2007) required ten iterations with each algorithm to solve each problem. Lozano et al. (2006) ran each algorithm 20 times in each benchmark case to ensure the validity of the global solution. However, repeating the algorithm several times cannot guarantee the best solution is at the global optimum if the search space does not contain the true optimum solution.

Consequently, some researchers attempt to overcome this problem by improving GA based on the search space reduction to find for the optimum points of feasible solution. Ndiritu and Daniell (2001) used fine-tuning and hill-climbing strategies based on the search space reduction to improve the binary-coded GA for rainfall-runoff model calibration. Fine-tuning strategy reduces the search space using the distribution of the best performing individual of the current generation based on the reduction of the starting range which is defined as Equations (2.34) and (2.35).

The new range limits after generation “g” are:

$$x\max_{i,(g+1)} = xb_{i,g} + re_i(x\max_i - x\min_i)\text{; (i.e. new upper bound)} \tag{2.34}$$

$$x\min_{i,(g+1)} = xb_{i,g} - re_i(x\max_i - x\min_i)\text{; (i.e. new lower bound)} \tag{2.35}$$

where $x\max_{i,(g+1)}$ and $x\min_{i,(g+1)}$ are the values of the parameter x_i, for the upper and lower bounds of the new limit, respectively, $xb_{i,g}$ is the value of parameter x_i for the best performing individual in generation g, *re* is the reduction rate (between 0.4-0.5) calculated using the ratio of new range and starting range, $x\max_i$ and $x\min_i$ are the search range limits before fine-tuning at the start of the optimisation i.e. initial boundary.

Hill-climbing strategy reduces the search space using the shift ratio (sh_i) based on the initial range reduction which is defined as Equations (2.36) and (2.37).

The new range limits after generation g then becomes:

$$x\max_{i,(g+1)} = x\max_i + sh_i(x\max_i - x\min_i)\text{; (i.e. new upper bound)} \tag{2.36}$$

$$x\min_{i,(g+1)} = x\max_i - sh_i(x\max_i - x\min_i)\text{; (i.e. new lower bound)} \tag{2.37}$$

where sh_i is the ratio of the best individual range (between the last and current generation) and the range of the initial boundary, $x\ max_i$ and $x\ min_i$ are the search rage limits of the initial boundary. The new upper and lower bounds of the search space are then updated after a given number of generations. The results showed that the GA with fine-tuning and hill climbing were achieved at global optimum while the standard GA failed in all runs.

Similar to fine-tuning strategy in Ndiritu and Danielle (2001), Liu (2012) used an adaptive boundary genetic algorithm (ABGA) to improve the real coded GA. The main difference is ABGA reduced the search space using the distribution of the new limit bounds around its mean value over the whole population of the current generation, defined as Equations (2.38) and (2.39).

The new range limits after generation g were:

$$x\max_{i,(g+1)} = x\max_{i,g} - c(x\max_{i,g} - xmean_{i,g}) \tag{2.38}$$

$$x\min_{i,(g+1)} = x\min_{i,g} - c(x\min_{i,g} - xmean_{i,g}) \tag{2.39}$$

where $x\max_{i,(g+1)}$ and $x\min_{i,(g+1)}$ are the value of the parameter x_i, for the upper and lower bounds of the new limit, respectively, $x\max_{i,g}$ and $x\min_{i,g}$ are maximum and minimum values of the whole population in the current generation, respectively, $xmean_{i,g}$ is the mean value of the whole population for the parameter x_i, c is a reduction rate which is a fixed small positive number, 0<c<1. The performance of ABGA was compared to the standard GA by using Shaffer's F7 (Schaffer, 1989) which is popularly used for benchmarking the GA performance and its global optimum is known as zero, defined as Equation (2.40).

$$f(x_1, x_2) = (x_1^2 + x_2^2)^{0.25}[\sin^2(50(x_1^2 + x_2^2)^{0.1} + 1.0] \tag{2.40}$$

The performance of ABGA is better than the standard GA both in terms of the mean number of trials to find the global optimum and the percentage of runs the algorithm succeeded.

However, their studies used the standard function for the optimisation problem and its global optimum point is known, thus the starting bounds could be set close to the point. Therefore, using these search space reduction techniques could enhance GA to find the global optimum solution. However, in the complex optimisation in real world problems, the global optimum point is unknown and the appropriate setting of the bounds is a challenge. These strategies of search space reduction attempt to update the new constraint boundaries for the new generation of interval algorithm for improving the optimal points of feasible solution. However, if the optimal points are outside the search space at the starting points of the algorithm, reducing the search space for the next generation of interval algorithm may not result in the global optimum. This thesis has therefore proposed a new GA technique known as dynamic genetic algorithm (DGA), developed for the purpose of reservoir optimisation. The new DGA will be discussed in section 3.3.

2.6.4 Multi-objective optimisation- brief introduction

The previous sections dealt largely with single objective problems but most practical situations of reservoir operation involve multi-reservoir, multi-objective systems. For example, the multiple objectives could be to maximise reliable and total energy output whilst considering other needs such as flood prevention, minimising water losses and other downstream impacts. Multi-objective optimisation (MO) techniques are widely used in water resources management to solve such problems. Solutions of MO problems have also been attempted using LP, DP and NLP (Yeh, 1985). More recently, multi-objective evolutionary algorithms (MOEA) have been developed for solving complex water resources multi-objective problems, including rule curves optimisation for multi-reservoir systems (see e.g. Hurford and Harou 2014; Reed et al., 2012, 2013; Geressu and Harou, 2015).

2.7 Reservoir inflow forecasting

2.7.1 Inflow forecasting applications for reservoir management

The planning of reservoirs for various purposes including flood and drought control relies on the historic inflow data at the reservoir site. Due to natural variability and other factors (e.g. climate and land-use changes), however, the inflow situation when the reservoir is being operated will be different. It is therefore important that reservoirs are properly operated so that they continue to perform satisfactorily during changing hydro-climatology. Awareness of future input flows into reservoirs is the most important and valuable information that contributes to decision-making in managing and allocating the water resources at a reservoir. Under uncertain streamflow, water allocation management becomes more complex. Thus, for reservoir operation to be effective, accurate knowledge or forecasting of future inflows must be available. Accurate and reliable inflow forecasting data are important in planning, design, and management of reservoir operation for water allocation as well as flood and drought prevention.

Reservoir operation concerns taking decisions on water release from a reservoir based on the amount of water available vis-à-vis the demand placed on the system. The available water is the sum of starting period storage and the inflow expected during the period. Consequently, effective reservoir operation relies on reliable forecast of the inflow into the reservoir. There are various inflow forecasting techniques including hydraulic (routing) method (Mashriqui et al, 2014), time series analysis approach (Valipour et al., 2013), regression analysis (Othman and Naseri, 2011) and artificial neural network (ANN) (Mohammadi et al., 2005). However, this study has applied only ANN for the reservoir inflow forecasting because of its attributes as briefly outlined in Section 1.1; fuller details of the ANN will be provided in Section 2.7.2. The rest of the techniques are briefly discussed in this section.

2.7.1.1 Hydraulic (routing) method

Hydraulic method involves the numerical solutions of the St Venant equations (i.e. involving the continuity and the momentum equations) to calculate open channel flow (Moussa and Bocquillon, 1996) and based on the physic characteristic of the river channel. Hydraulic routing is commonly used to predict the movement of water once runoff reaches the channel system, thus it is used for flood forecasting (Mashriqui et al., 2014; Scharffenberg and Kavvas, 2011) and widely used in several software tools such as the Hydraulic Engineering Center-River Analysis System (HEC-RAS), MIKE11 (1-D model) and MIKE21 (2-D model). However, practical application of hydraulic method is complex and difficult to implement because of its high demand on computing technology and on the quantity and quality of input data (Tewolde and Smithers, 2006).

2.7.1.2 Regression analysis

Regression analysis is the most frequency used statistical technique for modelling relationships between variables (May and Tung, 1992). Statistical or regression analysis approach based on simple linear methods has been used for forecasting in hydrology (Ward and Folland, 1991) that assumes stationary in the data, despite the fact that hydrological data generating processes are non-stationary and nonlinear (Edossa and Mukand, 2012; Othman and Naseri, 2011). A linear regression model consists of the regression variables, dependent variables and regression coefficients. The objective is to predict a dependent variable based on an independent variable. Data for complex systems i.e. the association of three or more variables are investigated by multiple linear regression. If all the variables (dependent and independent) are in linear form, the regression is referred to as multiple linear regression. Often a nonlinear association between the variables is handled by transforming the variables into a linear form and applying multiple regression as it is easier to treat linear equations (Jain and Singh, 2003).

Regression analysis is one of the oldest and most frequently used methods in streamflow and rainfall forecasting because of its simplicity and its time effectiveness. For example, Ward and Folland (1991) forecasted rainfall in the North Nordeste of Brazil using multiple linear regression. The models were driven by the tropical Atlantic and Pacific sea surface temperatures, and they revealed that 50% rainfall variance or more could be forecasted with the statistical techniques. Badyalina and Shabri (2013) applied multi-linear regression for streamflow forecasting at ungauged sites in the province of Peninsular Malaysia. The results indicated that elevation, longest drainage path and slope were the best input for the model, and generated a best forecast R of 0.856. Shu and Ouarda (2008) used nonlinear regression for flood quantile estimation at ungauged sites in the province of Quebec, Canada. The NASH (Nash-Sutcliffe efficiency) value for the model was below 0.7 which indicates that quantile estimates obtained using the nonlinear regression model are poor quality.

However, the main disadvantages of linear regression are limitations in the shapes that linear models can assume over long ranges, possibly poor extrapolation properties, and sensitivity to outliers (Dhanoa et al., 2008). Linear models with nonlinear terms in the predictor variables curve relatively slowly, so for inherently nonlinear processes it becomes increasingly difficult to find a linear model that fits the data well as the range of the data increases (Guthrie et al., 2012). This means that linear models may not be effective for extrapolating the results of a process for which data cannot be collected in the region of interest. Therefore, alternative techniques have been developed for prediction of the complex nonlinearity and non-stationarity. Several investigators have been compared the performance of regression analysis to other forecasting techniques; these are discussed later in next section.

2.7.1.3 Time series model

Time series models are commonly used for forecasting in economics, business, etc., with a collection of data recorded as time series-weekly, monthly, quarterly, or yearly (George et al., 2008). They have also been used on hydrological time series because it is too complex to determine their exact mathematical model, and thus results provided by a forecasting model, based on simple linear methods have been unable to replicate existing trends in hydrological data (Zhang et al., 1998).

Stochastic model or time series analysis is the investigation of a distributed sequence of data for prediction of future values. Time series models are applicable for many hydrologic forecasting, particularly streamflow and precipitation. They have been used to develop mathematical models to generate synthetic hydrological data, to forecast hydrologic events, to identify trends in hydrological data, to fill in missing observations, and to extend short hydrologic records (Salas, 1993). In hydrology, common stochastic models are the Box-Jenkins models which are widely used in time series forecasting such as autoregressive (AR), moving average (MA), autoregressive moving average (ARMA), and autoregressive integrated moving average (ARIMA) processes (Box and Jenkins, 1970).

In time series forecasting, AR and MA models are used for linear time series. However, MR is not widely used alone but generally combined with AR, so called an ARMA model in order to increase efficiency and accuracy of forecasting (Fung and Chung, 1999). However, the ARMA model can be used for only stationary time series data, thus the ARIMA is a modified version of the ARMA model which can be applied to a non-stationary (i.e. has no fixed mean level) data series. The basic idea of ARIMA is to remove the trend term of series by difference elimination so that a non-stationary series can be transformed into a stationary one. ARIMA model has been widely applied in hydrological forecasting such as rainfall forecasting (Meher and Jha, 2013) and inflow forecasting (Mohammadi et al., 2005). Valipour (2012b) compared the ability of autoregressive forecasting between ARMA and ARIMA for monthly inflow of the Dez dam reservoir. The study used root mean square error for comparing both models; the results showed that the ARIMA model could forecast inflow with lower error than the ARMA model. However, some disadvantages are found in time series models, for example, its inability to predict data with noise and its inability to accurately forecast from small data sets (Tang, et al. 1991). Several research studies have concluded that ANN approach has a better generalisation capability than the time series models (Jain et al., 1999; Baareh et al., 2006; Mohammadi et al., 2005); these are discussed later in the next section. Consequently, time series modelling was not pursued further in this study.

2.7.2 Artificial neural networks (ANN)

An artificial neural network (ANN) is a flexible mathematical model that emulates the processing mechanism of the nervous system. The structure of ANN is similar to the human brain, which contains billions of neurons and interconnections and has the ability to learn, generalise, and decide (Kashani et al., 2007). An ANN is a network of parallel distributed information processing systems that relate an input vector to an output vector. The theory and mathematical basis of ANN has been well described by Shamseldin (1997). ANN is data-driven self-adaptive method that enables learning and generalisation from experience. It draws upon examples and captures complex functional relationships among the data even if the underlying relationships are unknown or hard to describe (Zhang et al., 1998), and was first used in the fields of cognitive science and engineering (Kaastra and Boyd, 1996).

Traditional forecasting methods using hydrologic, hydraulic and time-series models require specification of the functional relationship of the model which can be problematic (Zhang et al., 1998), which is why focus has recently shifted to the use of data-driven techniques that do not require knowledge of this functional relationship. Recently, neural networks have increased dramatically and are widely used in many different fields such as business, industry, science, and engineering. ANN has been introduced as an effective alternative tool for modelling nonlinear and non-stationary time series in hydrological forecasting such as rainfall estimation and forecasting (Hung et al., 2009; Machado et al., 2011), rainfall-runoff modelling (Wu and Chau, 2011), reservoir parameter prediction (Adeloye and De Munari, 2006), reservoir operation (Jain et al., 1999; Khayyun and Mustafa, 2012), inflow forecasting (Zhang et al., 1998; Mohammadi et al., 2005; Kim et al., 2009; Othman and Naseri, 2011; Edossa and Babel, 2012; Valipour et al., 2012a; Taghi et al., 2012), and reference crop evapotranspiration estimation (Adeloye et al., 2011; 2012).

Some research studies have compared the performance of time series models and regression analysis to ANN in the forecasting of inflow. In general, they found that the ANN model demonstrated better performance than regression-based models such as multiple linear regression and multiple nonlinear regression (Kashani et al., 2007; Shu and Ouarda, 2008; Seckin, 2011; Zakaria and Shabri, 2012). Moreover, the ANN models have many advantages over time series models. For example, the data used do not need to follow a Gaussian distribution. ANNs perform well even when limited data are available (Jain et al., 1999).

Jain et al. (1999) investigated ARIMA and ANN for one-month-ahead inflow forecasting. It was found that the high flows were modelled better through the ANN, while low values were better predicted through the ARIMA model. However, the average monthly deviation for all of individual years was less for the ANN model. Baareh et al. (2006) applied ANN and AR models for the river flow forecasting problem of the Black Water River near Dendron, Virginia, and the Gila River near Clifton, Arizona. Their comparative study found that ANN performed better with lower error than AR. Mohammadi et al. (2005) investigated the potential application of ANN for reservoir inflow forecasting by comparing the performance of three different methods—regression analysis, ARIMA, and ANN. The results show that the ANN models are effective inflow forecasting tools because the errors are less than those of the other methods. The above serves to introduce the plausibility of ANN modelling for inflow forecasting. Further details about ANN are presented in the next section.

2.7.2.1 The architecture of ANN

(i) The neuron

ANN contains a number of neurons or nodes that are arranged in an input layer, an output layer, and one or more hidden layers that can approximate a nonlinear relationship between input and output data sets inspired by the brain and nervous systems in biological organisms. The input layer nodes receive the information, process it, and pass it to the hidden layer, which also processes and passes it to the final output layer, as illustrated in Figure 2.14. ANN consists of three simple sets of rules i.e. multiplication, summation and activation. At the entrance of artificial neuron, the input is weighted. As shown in Figure 2.14, a single input neuron with scalar input (x) is transmitted through the connection which is multiplied by its corresponding weight (w). In the sum function, the weighted input is summed along with a neuron threshold value or bias (b) to form an output scalar (n). The bias provides an additional variable that can be adjusted to obtain the desired network performance (Rustum et al., 2007).

At the exit of the artificial neuron, the sum of previously weighted input and bias is transmitted through activation function (or transfer function) which produces the output (y), (Demuth and Beale, 2002) expressed as:

$$y = f(n) = f(wx + b) \tag{2.41}$$

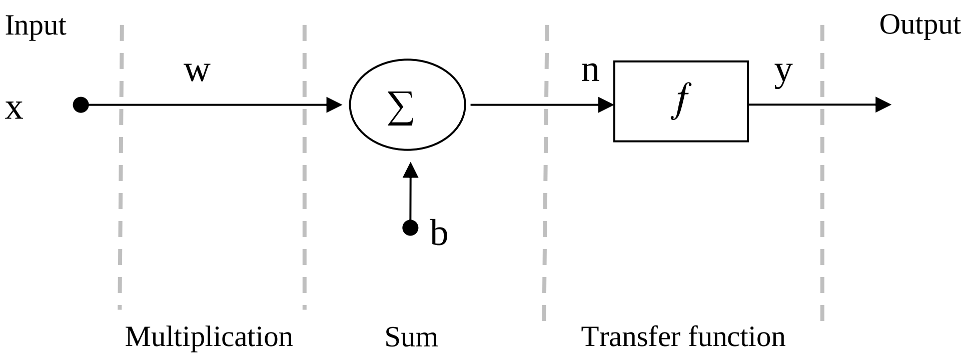


Figure 2.14 Schematic of single input neuron

In the multiple input neurons illustrated in Figure 2.15, the individual inputs (x_i, i=1, 2… r) are multiplied by weights ($w_{1,1}$, $w_{1,2}$,…, $w_{1,r}$). Similar to the single input neuron, the bias *(b)* is summed with weighted inputs to form the net input *(n)*, and then passed through the transfer function which produces the output *(y)*, expressed as:

$$y = f(n) = f(b_j + \sum_{i}^{r} x_i \times w_{j,i}) \tag{2.42}$$

Where *r* is the number of elements in input vector, $w_{,i}$ is the connection weight of the destination neuron *j* from the input neuron *i*.

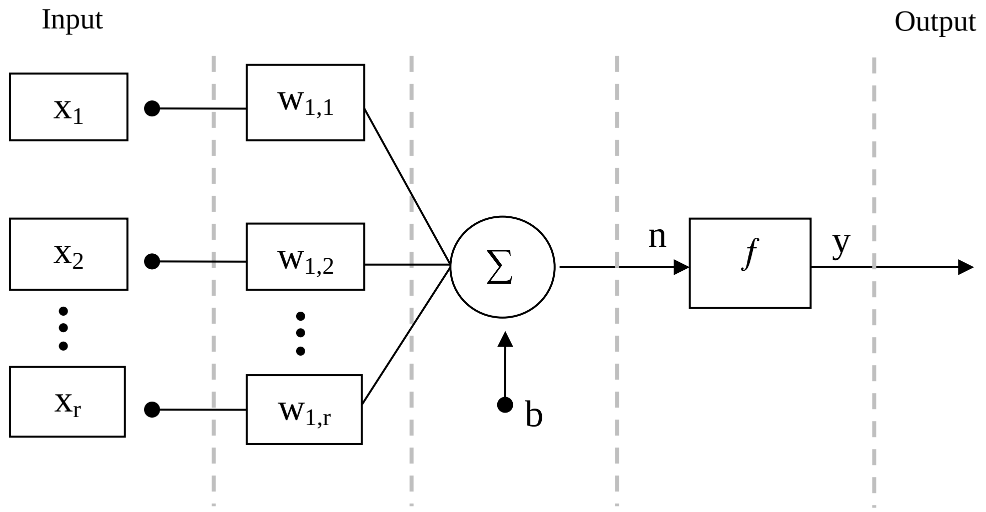


Figure 2.15 Schematic of multiple input neurons with a single hidden neuron

(ii) Transfer function

All neurons in the hidden layer and the output layer receive signals from each neuron in the previous layer. Each neuron in the network is operated by taking the sum of its weighted input, and passing the result through a transfer function to produce its result. The activation function or transfer function determines the relationship between inputs and outputs of a node and a network. It is used for transforming the neuron inputs into its single output and determining the output value. Thus the selection of an appropriate transfer function is an important issue in the application of multilayer perceptron (MLP) network. The choice of transfer functions depends on the complexity of the application. The most commonly used nonlinear functional forms of activation functions satisfying the approximation conditions of ANNs are logistic or sigmoid function (Shamseldin et al., 2002; Jain, et al., 1999; Yonaba, 2010) and hyperbolic tangent function (Zeng, 1999; Adeloye et al., 2006). The characteristics of sigmoid, tangent hyperbolic, and linear activation functions are given in Table 2.3 and these functions are presented as follows (Özkan and Erbek, 2003).

(1) Linear transfer function

In the linear transfer function, when n is the input to the neuron and y is the output after transmitting through the transfer function, the linear transfer function can be written as in Equation (2.43). The linear transfer function is particularly used for output layer function as it allows the output to take any value $(\pm\infty)$.

$$y = f(n) = n \tag{2.43}$$

(2) Sigmoid transfer function

Sigmoid transfer function is a simple activation that can introduce non-linearity to the network. It produces output in the shape of 'S' and the output ranges between 0 and 1. The most widely used of the sigmoid functions is the logistic or log-sigmoid, and defined as follow:

$$y = f(n) = \frac{1}{1+e^{-n}} \tag{2.44}$$

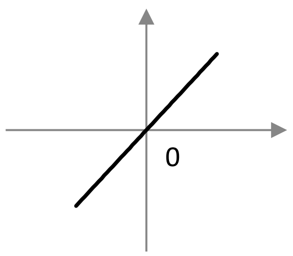
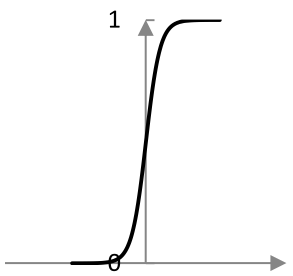
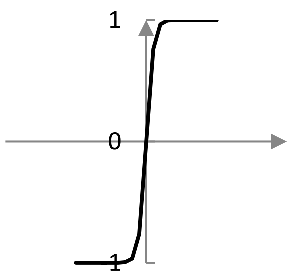
(3) Hyperbolic tangent function

Hyperbolic tangent function is the second most widely used for transfer function (Özkan and Erbek, 2003), similar to sigmoid function. It is a bipolar version of the sigmoid function with outputs ranging between -1 and 1, and produces output in the shape of 'S. This function is easily defined as the ratio between the hyperbolic sine and the cosine functions; it is also called tan-sigmoid and defined as follows:

$$y = f(n) = \frac{1-e^{-2n}}{1+e^{-2n}} \tag{2.45}$$

In the hydrological field, hyperbolic tangent function is widely used for the transfer function in hidden layer. For example, the study of Adeloye et al. (2006) has applied ANN based generalised storage-yield-reliability, the hyperbolic tangent function and linear function were selected for the transfer functions in the hidden layer and the output layer, respectively. The hyperbolic tangent function which is symmetric was preferred to the logistic function because MLP can learn faster when the function is symmetric than when it is asymmetric. Yonaba et al. (2010) have tested the different sigmoid transfer functions for neural networks in the multistep-ahead streamflow forecasting. The results showed that tangent sigmoid function in the hidden layer and linear function in the output layer required less computational time and provided higher correlation in training and testing performance than other transfer functions. In addition, usage of a nonlinear transfer function in the output layer failed in improving performance values.

Table 2.3 Activation function (Özkan and Erbek, 2003)

Activation function	2D graphical representation
Linear	
Sigmoid (logistic)	
Hyperbolic tangent	

2.7.2.2 Structural Categorisation

The most common method of classifying ANNs is based on the number of layers—single layer, bilayer, and multilayer. For example, in Figure 2.16 (a) and (b), the structure of the multilayer perceptron network consists of three layers; one input layer, one hidden layer and one output layer with a single output neuron. A hidden neuron layer can contain more than one neuron and it does not need to equal the number of input neurons. As discussed previously, ANN consists of a number of interconnected processing neurons. The way that individual neurons are interconnected to form a network is called topology or architecture of an ANN. Neural network can be classified according to their structures that are divided into two basic types: feed-forward and recurrent networks (Pham and Liu, 1995).

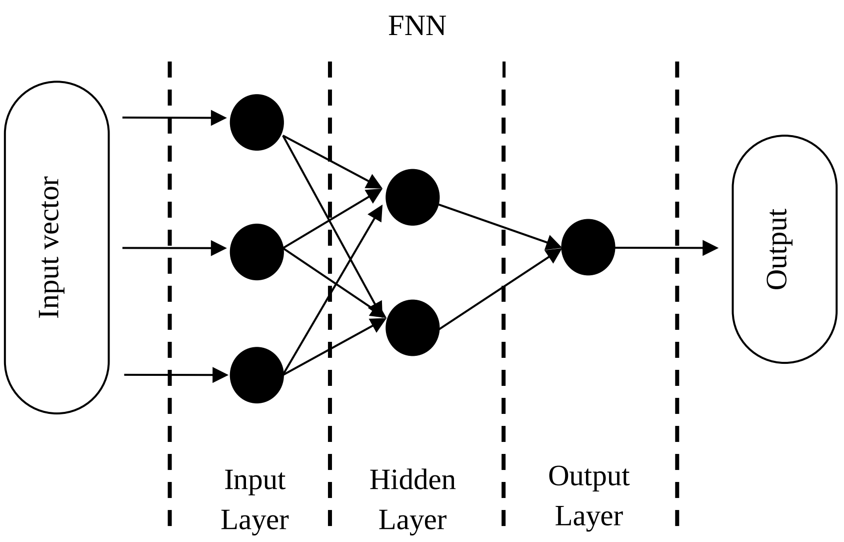
(i) Feed-Forward Neural Networks (FFNN)

ANN with feed-forward topology is called feed-forward artificial neural networks that information passes forward from input layer to output layer in only one direction with no back-loops. The neurons are connected from one layer to the next, but not within the same layer and no limitations on number of layers. Multi-layer perceptron (MLP) is perhaps the best known type of feed-forward networks (Pham et al., 2012). Simple multi-layer feed-forward artificial neural network (MLFFN) is illustrated in Figure 2.16 (a). This type of ANN generally performs static mapping of the input vectors to their corresponding outputs. MLFFN is the most popular and widely used in many applications such as forecasting (Zhang et al., 1998; Senthil Kumar et al., 2012; Gong et al, 2012). This is because it has been shown to have the best performance with regard to input-output function approximation (Jain et al., 1999; Shamseldin et al., 1997) and it has good learning and generalisation abilities (Gong et al, 2012).

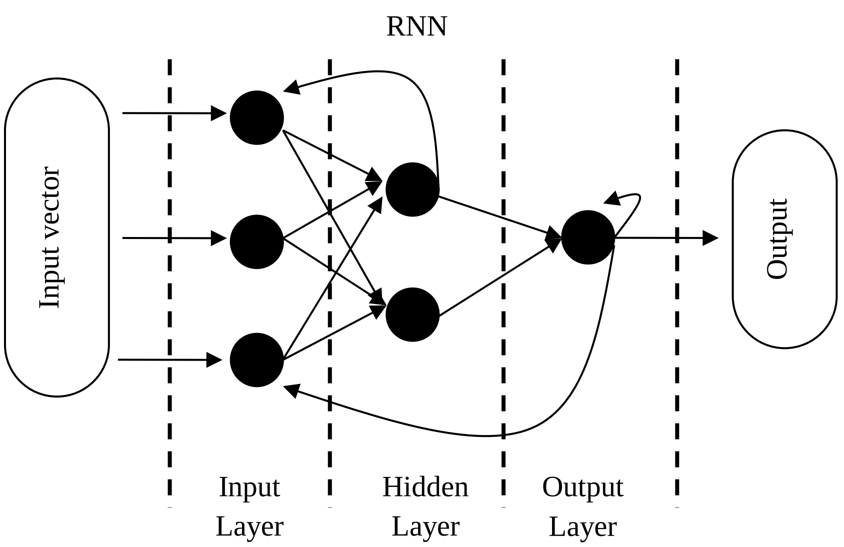
(ii) Recurrent Neural Network (RNN)

ANN with the topology is called a recurrent artificial neural network. It is similar to FFNN with no limitation of back-loops i.e. the information can flow in both forward and backward directions. RNN is called recurrent because it performs the same task for every element of a sequence, with the output depending on the previous computations.

RNN can be multi-layer or single layer fully or partially recurrent artificial neural network where every artificial neuron is directly connected to every other neuron in all directions (Krenker et al., 2011). Figure 2.16 (b) illustrated the partially RNN where some of the information flow is in two directions from input to output and also in the opposite direction.



(a)



(b)

Figure 2.16 An example of multi-layer perceptron (a) FFNN and (b) partially RNN.

2.7.2.3 Learning Algorithm Categorisation

After the topology of ANN is built, the next step is to learn the proper response of ANN and this can be achieved through learning algorithm. Learning algorithm is the process in which the weights and biases in ANN are adjusted in response to input-output training data set (Rustum et al., 2007). The learning process enables the network to search a set of weights that will produce the best possible input/output mapping. Normally, the learning process is achieved by minimising of the error between the network output and the target or desired output. Two main types of learning algorithm are supervised and unsupervised learning algorithms (Pham and Liu, 1995).

2.7.2.3.1 Supervised learning algorithms

Supervised learning requires a teacher or supervisor to match pairs of input and desired output values. Then it enables to adjust the weights according to the difference between the desired outputs and network outputs corresponding to a given input. The difference between the desired and network output which is called the error, is calculated. The weights are adjusted by each training iteration (epoch) until the error reaches an acceptable level or a maximum number of epochs is reached, and the current set of weights and biases are assumed to be optimal. Figure 2.17 illustrates a schematic representation of supervised learning. One of the most popular use for the supervised learning algorithm is back-propagation algorithm (Zhang et al., 1998; Cilimkovic, M., 2011) which will be described next.

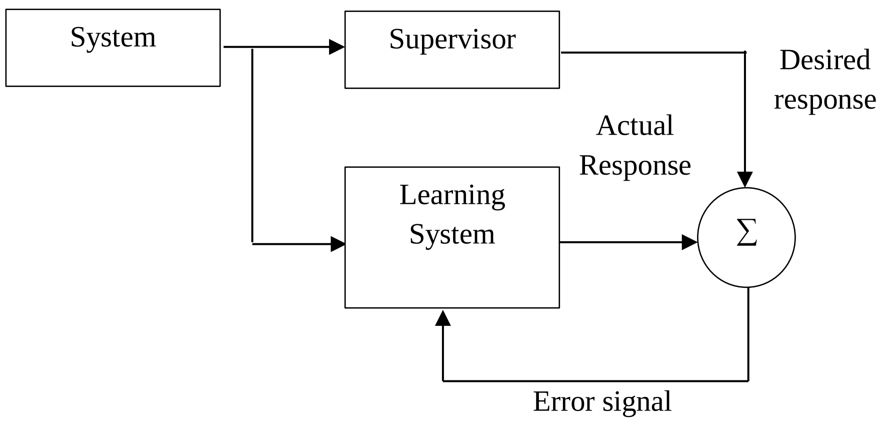


Figure 2.17 Schematic representation of supervised learning

(i) Back-propagation algorithm

Back Propagation (BP) algorithm performs parallel training for improving the efficiency of Multilayer Perceptron (MLP) network. The feed-forward multilayer perceptron (FFMLP) artificial neural networks are trained with the BP algorithm. BP neural networks are known to be very effective for capturing the no-linear relationship that may exist between input-output variables in complex system (Lippmann, 1987). BP searches for the minimum of the error function in weight space using the gradient descent method (or steepest descent method). In this method, the network starts with randomly generation generated weights, and then the weights are exposed to a training set of input-output data. The weights and biases are adjusted at each epoch in the direction that performance function decreases in order to minimise the objective function, e.g. mean square errors between the network output and desired output.

The basic BP neural network consists of; (1) MLP, (2) feed-forward processing, (3) Supervised learning, (4) transfer function and (5) minimising error criteria (Burton, 1998). The learning process of BP algorithm follows two main steps; i.e. forward pass and backward pass. In the forward pass, the predicted outputs are generated, corresponding to the given inputs. In the backward pass, partial derivatives of minimising error criterion with respect to adjusting weight coefficients are propagated back through the network (Mia et al, 2015). It iteratively adjusts the network parameters to minimise the sum of the square of the deviation between the observed output and predicted output (Sibi et al., 2013). These two processes are repeated until the error of the network is minimised. For forecasting application, the training data set consists of input signals (x_1 and x_2) assigned with corresponding target or desired output *(d)*. During training, the output predicted by the network $y_i(t)$ is compared with the target output $d_j(t)$ and the mean square error (MSE) between the two is calculated. The error function at time *t*, *E(t)* is given by Equation (2.47) (Maier and Dandy, 1996).

$$E(t) = \frac{1}{2}\sum_{i=1}^{N}\left(y_i(t) - d_i(t)\right)^2 \qquad (2.46)$$

where *N* is the number of data points. Then the error is propagated back to adjust the weights (w_{ji}) using Equation 2.47:

$$w_{ji}(t+1) = w_{ji}(t) + \Delta w_{ji}(t) \tag{2.47}$$

The weight increment, Δw_{ji} is calculated using Equation (2.48), in which the gradient descent method is applied. This results in weights being changed in the direction of steepest descent down the error surface. The size of the step taken down the error surface is determined by learning rate, η.

$$\Delta w_{ji} = \eta \frac{\partial E}{\partial w} \tag{2.48}$$

The learning rate η affects network-teaching speed. It can be very sensitive to the choice of the learning rates i.e. small learning rates tend to slow the learning process while larger learning rates may cause the algorithm to oscillate in the weight space and become unstable (Moreira and Fiesler, 1995). However, the gradient descent algorithm is often too slow and not robust enough for practical problems (Zhang et al., 1998) due to temporal stability and tendency to become stuck at local minima (Coulibaly et al., 2000). Later, high performance algorithms used standard numerical optimisation techniques for neural network training i.e. Levenberg-Marquardt algorithm (Marquardt, 1963; Levenberg, 1994) which can converge faster than the standard BP (gradient descent algorithm).

a. Levenberg-Marquardt (LM) algorithm

LM algorithm provides a numerical solution to the problem of minimizing a nonlinear function. It is fast and has stable convergence. In the artificial neural-networks field, this algorithm is suitable for training small- and medium-sized problems (Yu and Wilamowski, 2011). The Levenberg–Marquardt algorithm combines the steepest descent method and the Gauss–Newton algorithm. The slow convergence of the steepest descent method can be greatly improved by the Gauss–Newton algorithm; i.e. using second-order derivatives of error function to “naturally” evaluate the curvature of error surface. Hence, the Gauss–Newton algorithm can find proper step sizes for each direction and converge very fast.

The derivation of the Levenberg–Marquardt algorithm is presented in the following steps. The steepest descent algorithm is a first-order algorithm. It uses the first-order derivative of total error function to find the minima in error space, combining Equations (2.47) and (2.48), and is presented as:

$$w_{ji}(t+1) = w_{ji}(t) + \eta \frac{\partial E}{\partial W}(t) \tag{2.49}$$

Normally, gradient g is defined as the first-order derivative of total error function:

$$g = \frac{\partial E}{\partial w} \tag{2.50}$$

Compared with the steepest descent method, the second-order derivatives of the total error function need to be calculated for each component of gradient vector. As the second-order derivatives of total error function, Hessian matrix H gives the proper evaluation on the change of gradient vector, g.

$$\Delta w_{ji} = -H^{-1} g \tag{2.51}$$

If Newton's method is applied for weight updating, in order to get Hessian matrix *H*, the second-order derivatives of total error function have to be calculated and it could be very complicated. In order to simplify the calculation process, the Jacobian matrix *J* is introduced as and the gradient can be computed as:

$$g = J^T e \tag{2.52}$$

where *J* is the Jacobobian matrix that contains first derivatives of the network errors with respect to the weights and biases, ^{T} is used to denote transposition and e is a vector of network errors.

As the basic assumption of Newton's method, the relationship between Hessian matrix *H* and Jacobian matrix *J*, Hessian matrix *H* can be approximated as;

$$H \approx J^T J \tag{2.53}$$

By combining Equations (2.47) and (2.51), the update rule of the Gauss–Newton algorithm is presented as:

$$w_{ji}(t+1) = w_{ji}(t) - (J^T J)^{-1}(J^T e) \tag{2.54}$$

In order to make sure that the approximated Hessian matrix $J^T J$ is invertible, Levenberg–Marquardt algorithm introduces another approximation to Hessian matrix:

$$H = J^T J + \mu I \tag{2.55}$$

where μ is always positive, called combination coefficient and I is the identity matrix. The Levenbergh-Marquardt algorithm uses this approximation to the Hessian matrix by combining Equations (2.47) and (2.55), the update rule of Levenberg–Marquardt algorithm can be presented as

$$w_{ji}(t+1) = w_{ji}(t) - (J^T J + \mu I)^{-1}(J^T e) \tag{2.56}$$

As the combination of the steepest descent algorithm and the Gauss–Newton algorithm, the LM algorithm switches between the two algorithms during the training process (Yu and Wilamowski, 2011). When the combination coefficient μ is very small (nearly zero), the Gauss–Newton algorithm is used. When the combination coefficient μ is very large, this becomes the steepest descent. Thus μ is decreased after each successful step (i.e. reduction in performance function) and is increased only when a tentative step would increase the performance function (i.e. error increases). In this way, the performance function will always be reduced at each iteration of the algorithm (Demuth and Beale, 1998). Thus the LM method is the standard method for minimisation of the MSE criterion, due to its robustness and rapid convergence on networks which contain up to a few hundred weights, which makes it attractive in ANN training.

ANN trained using the LM algorithm has been used in various field of hydrology such as reservoir inflow forecasting (Othman and Naseri, 2011; Kim et al., 2009), streamflow forecasting (Edossa and Babel, 2012; Teschl and Randeu, 2006), predicting the capacity of water supply reservoir (Adeloye, 2009) and predicting within-year and over year reservoir capacities (Adeloye and De Munari, 2006).

(ii) Over-fitting

One of the problems occurring during neural networks training is called over-fitting. In case of over-fitting, the mapping ability of neural networks can lead to a very accurate fit of the training data (very small error on the training set), but when new data are tested the result is poor performance (large error) (Demuth and Beale, 1998). There are some methods that have been used to avoid over-fitting such as increasing the sample size (Amari et al., 1997), pre-processing and post-processing (Jayawardena, 2014), and early stopping approach (Adeloye et al., 2006).

a. Sample size

The simple way to achieve generation is using enough training data (Sahiner et al., 2008). If the sample size of data can be increased by collecting more data, then the training set will increase, so there is no need to worry about over-fitting. This is because a large sample size decreases the noise effects and improves generalisation of the network (Rustum et al., 2007). The study of Amari et al. (1997) showed that no over-fitting was observed when the ratio of the sample size to the number of weights in the networks was larger than 30. Wang et al. (2005) found slight over-fitting when the ratio of the sample size to the number of weights in the networks was larger than 50. There is, however, no universal rule to avoid over-fitting for all problems.

b. Pre-processing and post-processing

This method is used for scaling all signals, both input and output, to the same variance. Therefore, all signals are equalised to ensure that all the input signals apply the same influence throughout the training process. Where there is seasonality, it has been found that removing such seasonal patterns from the original times series can improve the accuracy (Mulia et al., 2015). Removing seasonality of the input data tends to make the training process more efficient computationally and reduces the chances of being trapped in local optima (Jayawardena, 2014). Therefore, data normalisation is often performed before the training process begins, and is called pre-processing (Zhang et al., 1998). After the network has been trained, the outputs of network have to be converted back into the same units that were used for original targets, which is called post-processing. The outputs are denormalised using the inverse of the pre-processing transformation. The approach for scaling network data set is to normalise it in which it will have zero mean and unit variance. The input and target variables are treated independently and for each variable (x_i). The normalisation is defined as:

$$x_{i-nor} = \frac{x_i - \bar{x}}{\sigma} \tag{2.57}$$

where x_{i-nor} is a normalised variable, $\bar{x}$ is mean and σ is standard deviation.

c. Early stopping rule (ESR)

The early stopping rule (ESR) is widely used in practise to overcome the over-fitting problem and to find the network having the best performance on new data (e.g. Rustum and Adeloye, 2012; Piotrowski and Napiorkowski, 2013). In some cases, this approach can improve the generalisation on capability of the trained network. To implement ESR in practice, the available data are divided into three parts (Adeloye et al., 2006):

- A training set, used to determine the network weights and biases;
- A validation set, used to estimate the network performance and decide when the training is stopped;
- A test set, used to verify the effectiveness of the stopping criterion and to estimate the expected performance in the future.

Generalised performance is measured on the testing set. The test set error is not used during training, but it is used to compare different models. The cross validation set is used to monitor the error variation during training process. As seen in Figure 2.18, during the initial phase of training, the validation error and the training error normally decrease. However, the validation error typically begins to rise when the network begins to overfit the data. Training automatically stops when generalisation stops improving, as indicated by an increase in the mean square error (MSE) of the validation samples as illustrated in Figure 2.18.

As noted earlier, this cross-validation early stopping is the most popular method to achieve generalisation (Wang et al., 2005). Coulibaly et al. (2000) investigated the Levenberg–Marquardt Back propagation (LMBP) with early stopping approach for real-time reservoir inflow forecasting. The results indicated that the method can provide better and reliable generalisation performance than the use of LMBP alone. The use of early stopping reduced the training time and it is effective for improving prediction accuracy. Adeloye et al. (2006) developed the storage-yield-reliability models for reservoirs using MLP-ANN, trained by the early stopping approach with the Levenberg-Marquardt algorithm. The study investigated the use of ANN for simultaneously predicting within-year and over-year reservoir capacities. The results showed that the performance of the models was very good and ANN was recommended.

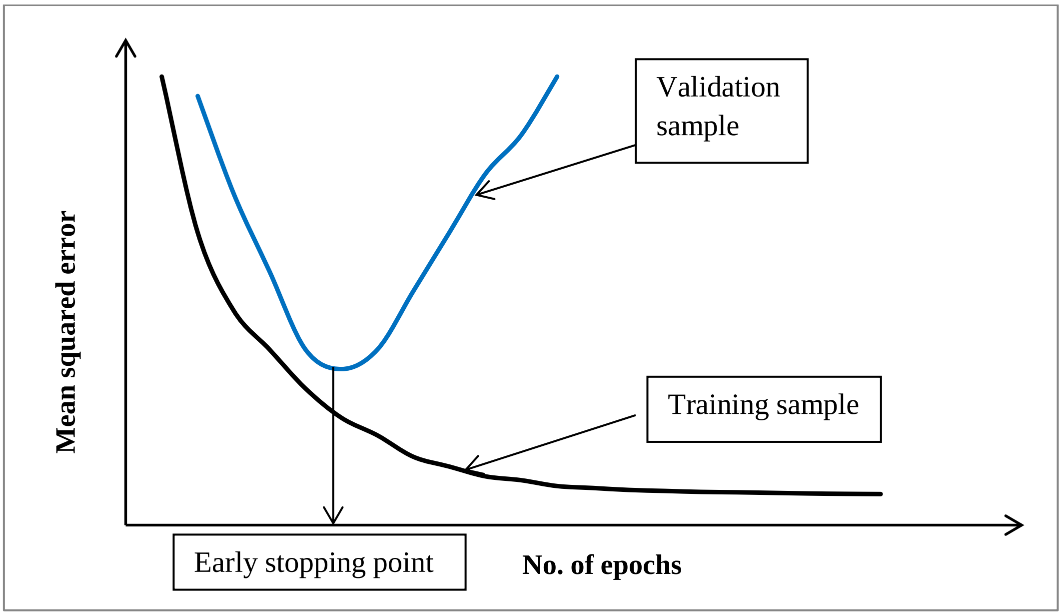


Figure 2.18 Illustration of cross-validation early stopping (Jayawardena, 2014)

(iii) Selection of the network elements

In the network structure of MLP, commonly all input nodes are in one input layer, all output nodes are in one output layer and the hidden nodes are in one or more hidden layers. To create an MLP, the variables have to be determined; these are the number of input nodes, the number of hidden layers and hidden nodes, and the number of output nodes.

a. The number of input neurons

The number of input nodes is one of the most important decision variables for a time series forecasting model, so it contains the important information about the complex (linear or nonlinear) autocorrelation structure in the data. Too few or too many input nodes can affect either learning or prediction capacity of the network. Tang et al. (1991) used 12 inputs and reported the benefit of using more inputs nodes, while Lachtermacher and Fuller (1995) found a negative impact of using more input nodes for single-step-ahead forecasting, but a positive impact on multi-step prediction. In a time series-forecasting model, the number of input nodes corresponds to the number of lagged observations used to discover the underlying pattern in a time series and to make forecasts for future values (Zhang et al. 1998). Therefore, the input parameters or input nodes in ANN forecasting can be determined by the number of lags in nonlinear time series analysis to improve the neural network model building process.

Lagged correlation refers to the correlation between two time series shifted in time relative to one another. Autocorrelation (ACF), partial autocorrelation (PACF) and cross correlation (CCF) analysis are commonly used to identify the correlated input for the forecast model; their formulas are presented in George et al. (2008). ACF is used to determine the level of dependence between successive data values, the correlation between two variables; the original time series and the lagged number of it. PACF can be used to determine which model type would best fit the data. PACF measures the linear dependence of one variable after removing the effect of other variable(s) that affect both variables. CCF is a standardized measure of association between values in one time series and those of another time series. In the relationship between two-time series (Y_t and X_t), the series Y_t may be related to past lags of the X-series. CCF is helpful for identifying lags of the X-variable that might be useful predictors of Y_t.

b. The number of hidden neurons

A single hidden layer is sufficient for ANN to approximate any complex nonlinear function (Mulia et al., 2015) and it is commonly used for forecasting purposes in several research studies (Zhang et al. 1998). However, one hidden layer may require a large number of hidden neurons. A small number of hidden neurons in a model provides good generalisation, but too few neurons can result in poor approximation and too many neurons may cause overfitting problems (Ding et al., 2011; Mulia et al., 2015). Therefore, some researchers have provided empirical rules to restrict the number of hidden neurons e.g., using $2n+1$ (Lippmann, 1987; Hecht-Nielsen, 1990), $2n$ (Wong, 1991), n (Tang and Fishwick, 1993) and $n/2$ (Kang, 1991; Eberhart and Dobbins, 1990), where n is the number of input nodes. However, none of these heuristic choices works well for all problems.

The number of neurons in the hidden layer is much more difficult to arrive at and is normally determined as part of the training by trial and error as described by Adeloye and De-Munari (2006). Therefore, the most common way in determining the number of hidden nodes is via experiments or by trial-and-error. (Zhang et al., 1998; Mohammadi et al., 2005; Kim et al., 2009).

c. The number of output neurons

The number of output nodes is specified with regard to the problem of the model. There are two type of forecasting: one-step-ahead (which uses one output node) and multi-step forecasts. The multi-step forecasts can use either one output node or several output nodes (Zhang, 2004). If one output node is employed for multi-step-ahead forecasts, the iterative forecasting approach is assumed and the forecast values are iteratively used as inputs for the next forecasts. Conversely, if the number of output nodes is equal to the length of the forecasting horizon, then the future values are forecasted directly from the network outputs (Pao, 2006).

(iv) Selection of the proportion of data ratio

Based on the literature review, most of the publications have focused on the training technique and activation function form to enhance the convergent rate and forecasting performance. Besides those techniques, only a few research studies have investigated the sensitivity of the proportion of data ratio (training, validation and testing set) for ANNs. For example, Yadav et al. (2011) investigated the sensitivity of the ANN prediction model of long-term streamflow forecasting; three different proportions of ratio were analysed, that is 60:20:20, 80:10:10 and 90:5:5 for training, validation and testing. The results showed that a low proportion for validation and testing (90:5:5) gives better results, with high accuracy. Therefore, the ratio of 90:5:5 recommended by Yadav et al. (2011) will be used in this study.

2.7.2.3.2 Unsupervised learning algorithms

As noted earlier, there are two main types of learning algorithm: supervised and unsupervised. In unsupervised learning algorithm, the learning process in which changes are made to the network’s weights and biases does not require the intervention of any external supervisor. Thus, the weights and biases are modified in response to network inputs only and there are no target outputs available (Demuth and Beale, 1998). Commonly, these changes are a function of the current network input vectors, output vectors, and previous weights and biases. One particularly interesting class of unsupervised system is based on competitive learning, in which the output neurons compete amongst themselves to be activated, with the result that only one is activated at any one time. This activated neuron is called a winner-takes all neuron or simply the winning neuron (Peng and Tu, 2005). Such competition can be induced/implemented by having lateral inhibition connections (negative feedback paths) between the neurons (Thomson and Emerly, 2014). The result is that the neurons are forced to organise themselves. The most widely used unsupervised neural network is the Self-Organising Map (SOM).

SOM is a competitive, unsupervised form of artificial neural networks pioneered by the Finnish professor, Professor Teuvor Kohonen (Kohonen et al., 1996). The information in a SOM is stored in such a way that any topological relationships within the training set are maintained. This implies that the SOM translates the statistical dependencies between the data into geometric relationship, therefore maintaining the most important topological and metric information contained in the original data (Rustum, 2009). The principal goal of the SOM is to transform an incoming signal pattern of arbitrary dimension into a two-dimensional discrete map. It involves clustering the input patterns in such a way that similar patterns are represented by the same output neurons, or by one of its neighbours (Adeloye, 2011). In this way, the SOM can be viewed as a tool for reducing the amount of data by clustering, thus converting a complex, nonlinear statistical relationship between high dimensional data into a simple relationship on low dimensional display (Kohonen et al., 1996). This mapping preserves the most important topological and metric relationship of the original data elements, implying that not much information is lost during the mapping.

Several studies e.g. Rustum and Adeloye (2007) and Kalteth and Hjorth (2009) have found that SOM performed better than most widely used Multi-Layer Perceptron Artificial Neural Networks (MLP-ANN) in water resources. SOM is also very robust to the missing data during its training (Malek et al., 2008) whereas MLP-ANN will require a complete data set for its training. Thus, if data are missing, an off-line pre-processing to provide estimates of the data in the input space is mandatory before the training of MLP-ANN can process (Rustum and Adeloye, 2007).

2.8 Summary

Reservoirs are generally designed and operated to store excess water during the wet season for later release during the dry season or drought periods when the demand is higher than the river flow. Based on their configurations, they can be classified into two types: single and multi-reservoir systems. Single reservoirs are operated independently of one another, but multi-purpose reservoir systems involve more than one reservoir, operating in an integrated manner. Based on their objective, they also can be classified into two types: single and multi-purpose reservoirs. If a reservoir has more than one purpose, it is called a multi-purpose reservoir.

Reservoir operation techniques are reviewed, distinguishing between SOP-based and zone-based. This chapter also reviewed the application of simulation models in reservoir operation. Simulation-optimisation techniques are also reviewed in the context of reservoir rule curves and hedging rules development. In the literature, it was found that the hedging policy is of benefit in reducing the impact of severe droughts. Hedging policy saves water during normal operation and uses this to augment supply during severe droughts.

However, to develop the reservoir rule curves or hedging policy, optimisation is required and available optimisation formulations and solutions scheme were also reviewed in the chapter. Of these, the genetic algorithm (GA) approach is most suitable for the optimisation and development of rule curves and has therefore been selected for the study. GA can be classified into two types: binary coded and real coded. Several researchers have demonstrated that real-coded GA has advantage over binary coded; these were discussed in section 2.6.3. However, as argued in this section, the main challenge of GA is establishing the optimal boundary of the feasible region to search for the optimal solution. Too wide or too narrow a boundary can lead the result of GA to trap on the local optimal solution. Examples of search space reduction techniques that have been developed to address this problem were reviewed.

Reservoir inflow is one of the important variables in the water balance of the reservoir system. The inflow is often unknown at the time of making the operational release decision; hence inflow forecasting is a major activity associated with reservoir operation. Reservoir inflow forecasting techniques were reviewed in section 2.7. In the literature, research has supported that artificial neural network (ANN) is an effective tool for forecasting. However, many challenges are found in ANN and these were also reviewed and discussed in this chapter.

A review of the widely applied performance criteria to describe the degree of reservoir operation failure was undertaken in this chapter. These are reliability, resilience, vulnerability and sustainability. Reliability measures either the proportion of time or the volume that the reservoir performed successfully; the resilience is the ability of a reservoir system to recover from a failure, and vulnerability is a measure of magnitude of failure. The sustainability index integrates the three earlier defined indices. The next chapter presents the methodological approaches used in the research

Chapter 3 Methodology

3.1 Introduction

The whole methodological process is summarised in Figure 3.1. The data collection activity is straightforward and its details are the subject of chapter 4. The simulation optimisation modelling for rule curve and its hedging enhancement will use the SGA and the improved dynamic genetic algorithm (DGA) developed during this study. As noted earlier in chapter 2, the DGA is the main new development in the work; consequently, details of methodology will form the bulk of this chapter. The inflow forecasting will use the ANN and details about the ANN modelling, including analysis to isolate input factors are also presented in this chapter.

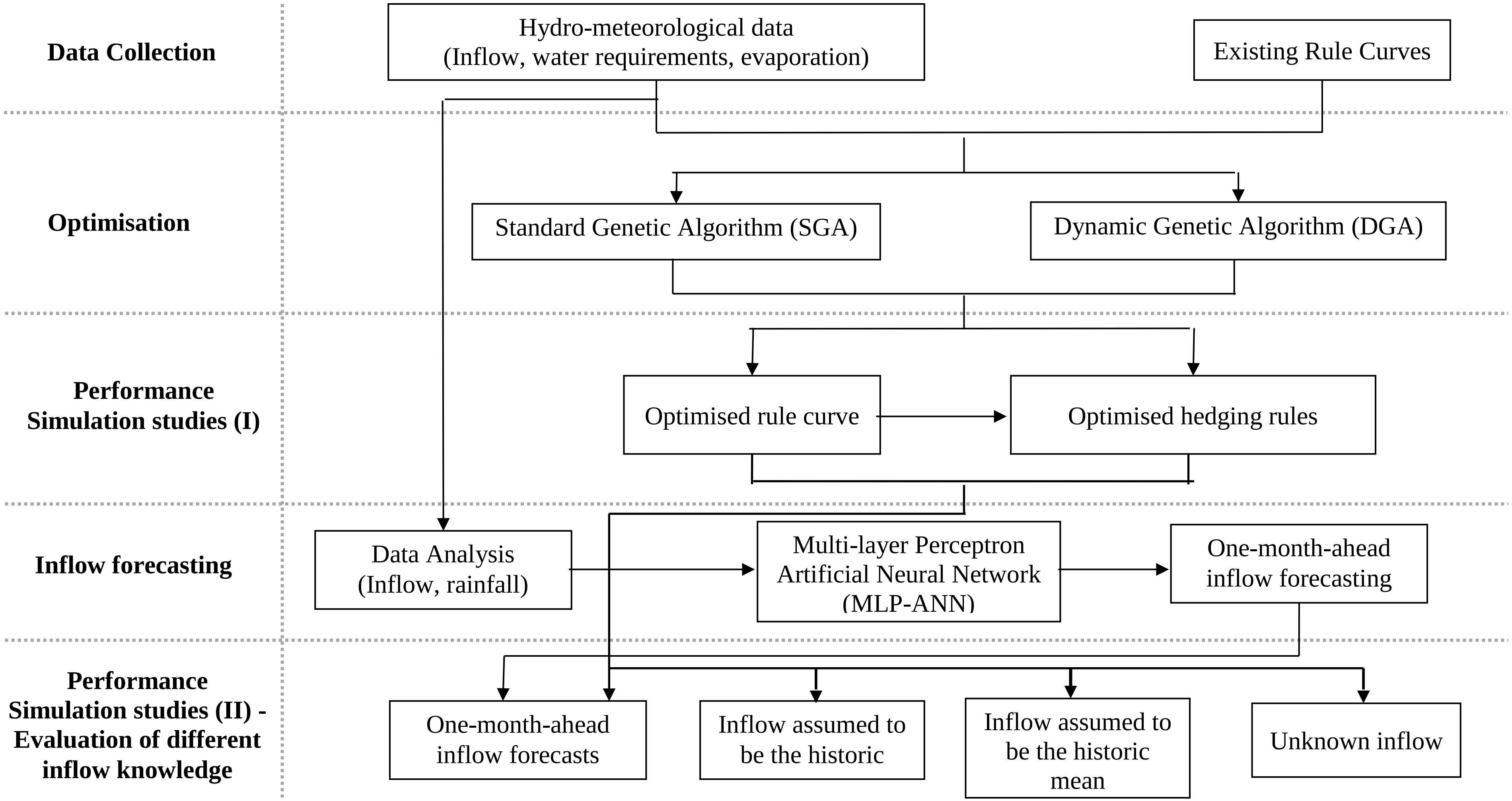


Figure 3.1 The methodology flowchart

3.2 Genetic algorithm optimisation of rule curves

3.2.1 Standard genetic algorithm (SGA)

As discussed earlier in the literature review, a genetic algorithm approach searches the results from a population of points and uses the operation of selection and evolution, so there is a greater possibility of arriving at the global optimum. Additionally, the results of the comparative studies (Reddy and Kumar, 2006; Azamathulla et al., 2008) in the literature have proved that GAs are better than other optimisation schemes (e.g. LP, NLP, and DP) in finding the global optimum for a complex problem. Therefore, GA was chosen for the optimisation in this study. The SGA is implemented according to the standard procedure of GA as described earlier in section 2.6.2. As discussed earlier in section 2.6.3, in this study the population is generated using real coding. The key GA's parameters used in this study are shown in Table 3.1. Another key GA parameter not included in Table 3.1 is population size (number of chromosomes) which specifies how many solutions are in each generation. In this study, the SGA algorithm investigated the effect of population sizes (50, 100, 200 and 250) and generations (1-3000) on the fitness values of the reservoir operating rule curves; its results are shown in next chapter.

Table 3.1 Setting for key GA's parameters

Key parameters	Value
Selection	roulette-wheel
Elite count	1
Crossover operator	Scattered crossover
Crossover fraction	0.8
Mutation	Uniform
Mutation rate	0.01

3.2.2 The dynamic genetic algorithm (DGA) for rule curve optimisation

As discussed in section 2.6.2, if search space is not in an optimal space, the standard GA may be trapped in a local optimum. Consequently, search space reduction techniques were developed to overcome this problem in SGA. The DGA is schematically illustrated in Figure 3.2. It starts with an initial random population like the SGA and runs over “g” generations from which the best string is selected. This process is repeated “r” times, thus leading to “r” best strings. Then “g” and “r” are parameters of DGA and their best values are determined by trial-and-error but, as will be seen later, are much lower than the g=3000 and r=100 normally required for the SGA. The best of the “r” strings are then observed for the purpose of updating the boundaries for the search space in the next algorithm.

3.2.2.1 The DGA process for a reservoir operation

The dynamic GA process is thus implemented as follows:

Step 1: An initial random population of chromosomes is generated as in SGA. A chromosome (solution) contains decision-variable values or genes within the initial constraint boundary (UB_i and LB_i).

Step 2: The fitness value (or objective function) for each solution is evaluated.

Step 3: A new population is created by implementing GA three fundamental operations -selection, crossover, and mutation. The best solution in the current generation is obtained and its fitness value noted. This process is repeated over the selected number of generations (g) resulting in “g” best solutions. Isolate the best among these “g” best solutions.

Step 4: Repeat steps 1-3 until the specified number of repetitions (r) is completed, giving “r” best strings. As an illustration, suppose the number of generations “g” and the number of repetitions “r” are specified as 5 and 3, respectively, for a minimisation problem. The group of best solutions of each generation for 3 repetitions will be as shown in Table 3.2. In this Table, the fittest solution of the last generation is the best solution for each repetition. Comparing these three best solutions (numbers 5, 10 and 15), it is clear that overall best solution of the group is no.10 and its solution will be used to update the boundary for the next implementation of the algorithm (step 5).

Step 5: Update the boundaries for the search space for gene (X_i) of the next algorithm using the solution of step 4 as follows:

$$UB_{i,k+1} = Xb_{i,k} + 0.5(Xb\max_{i,k-1} - Xb\min_{i,k-1}), LB_i \le UB_{i,k+1} \le UB_i \quad (3.1)$$

$$LB_{i,k+1} = Xb_{i,k} - 0.5(Xb\max_{i,k-1} - Xb\min_{i,k-1}), LB_i \le LB_{i,k+1} \le UB_i \quad (3.2)$$

where $UB_{t+1,i}$ is the new upper boundary of i^{th} decision variable; $LB_{t+1,i}$ is the new lower boundary of i^{th} variable; $Xb_{i,k}$ is the value of the parameter x_i for the best performing individual of the current group (based on the best solutions from all repetitions); $Xbmax_{i,k-1}$ and $Xbmin_{i,k-1}$ are the maximum and minimum values of $Xb_{i,k-1}$ (the range of the best solutions from each repetition) in the past group; UB_i and LB_i is the initial upper and lower bounds, respectively of i^{th} variable. For the particular problem of upper and lower rule curves optimisation there are 24 decision variables, 12 each for the ordinates of the upper and lower curves respectively.

Step 6: Repeat steps 1-5 until the difference between best values for any two consecutive iterations is lower than a specified value "β", i.e. $FVAL_{k-1} - FVAL_k \le \beta$. In this study the stopping criterion "β" is 0.05. The "β" can be defined ≤0.05 if the fitness value is very small. On the other hand, the "β" can be defined ≥0.05 if the fitness value is very high.

Table 3.2: An example of a group of solutions in “g” = 5 and “r” = 3 (The best solution per repetition is circled)

Solution			Gene				Fitness value
No.	r	g	X_1	X_2	X_3	X_4	
1	1	1	51	90	56	86	5650
2		2	97	60	62	89	3860
3		3	54	76	61	91	2200
4		4	82	98	56	68	1750
5		5	53	85	93	75	1023
6	2	1	73	58	100	92	1220
7		2	94	60	59	75	830
8		3	82	85	85	71	702
9		4	53	83	52	96	650
10		5	92	51	69	87	596
11	3	1	92	60	53	57	2890
12		2	89	67	63	56	1980
13		3	85	68	68	97	1002
14		4	56	80	90	88	950
15		5	100	89	65	95	864

The key parameters of DGA are "g" and "r". "g" specifies the number of generations. With a small number of generations, the search space of new boundaries is gradually reduced thereby producing a better result. However, an excessively large number of generations may guide the algorithm to miss the optimal search space. "r" specifies the number of repetitions. Too few repetitions may not provide the representative solution, while too many iterations will increase the computational time. As noted earlier, best values for these parameters were determined by trial and error. Consequently, the DGA algorithm was tested for generations "g" (= 2, 5, 10, 15 and 20) and repetitions "r" (= 3, 5, 7 and 10); its results are shown in chapter 5.

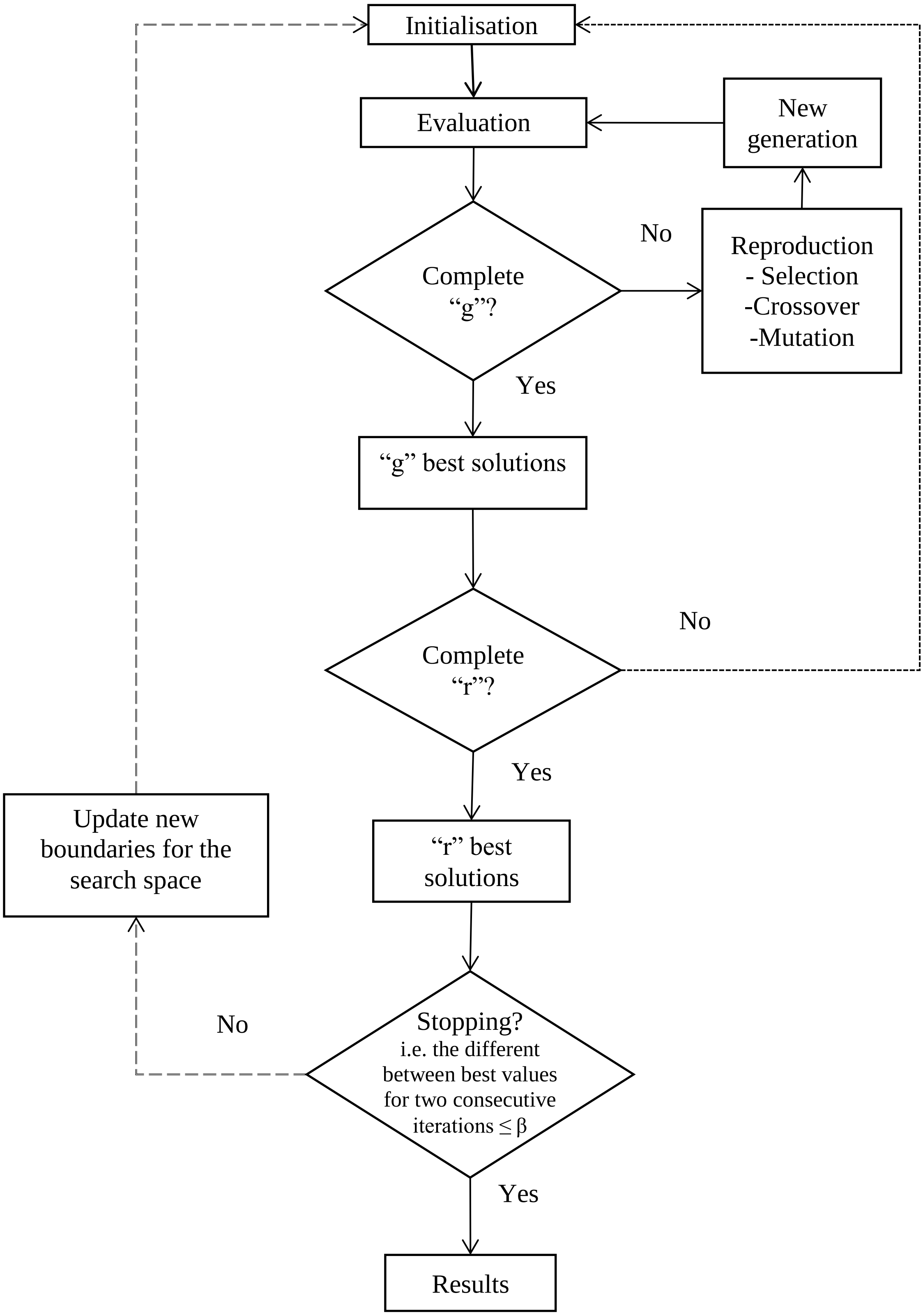


Figure 3.2. Dynamic genetic algorithm flowchart

3.2.2.2 Testing the new DGA formulation for reservoir rule curves

To test the accuracy of DGA, the performance of DGA was compared to the standard GA by using Shaffer's F7 (Schaffer et al., 1989) which was also used for benchmarking the GA performance in Liu (2010). In this study, the initial intervals are set in such way that the true minimum is located close to the centre of the search space, so the initial space is -100<x<100 and -100<y<100. The global optimum is known as zero at two variables (x, y) which are both zero, as defined in Equation (2.40) in section 2.6.2:

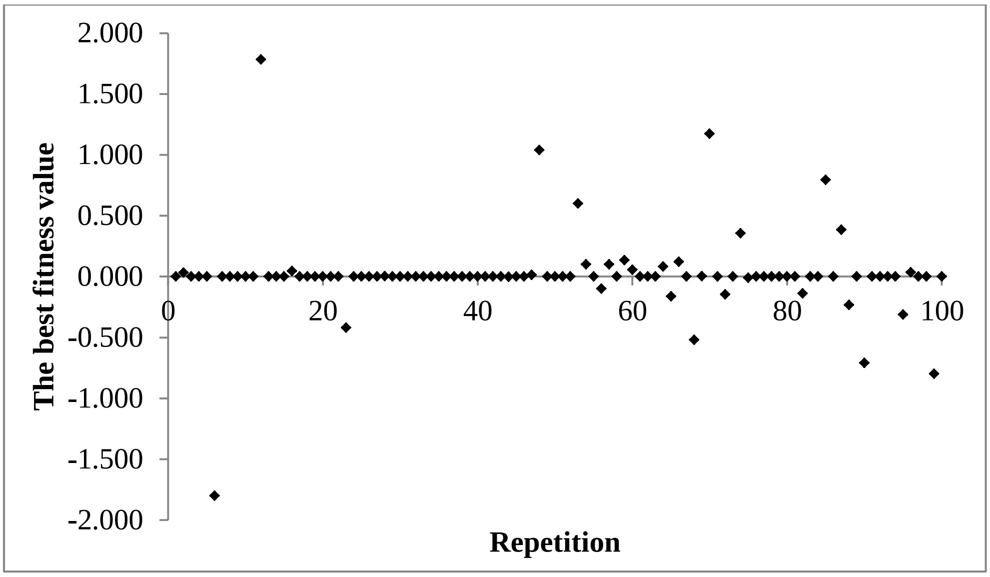
$$f(x_1, x_2) = (x_1^2 + x_2^2)^{0.25}[\sin^2(50(x_1^2 + x_2^2)^{0.1} + 1.0]$$

It has a large number of local optima, but only (0,0) is its global optimum point which provides the objective function is 0. The SGA and DGA were run 100 repetitions over the test function. The results of all repetitions in SGA and DGA are shown in Figure 3.3 (a) and (b), respectively and the relevant statistics are summarised in Table 3.3. As the results show that, there are 66 runs in SGA (Figure 3.3 (a)) and 94 runs in DGA (Figure 3.3 (b)) out of 100 in which the global optimum was successfully located. The best fitness values (f(x)) and the ordinates (x, y) for SGA and DGA are summarised in Table 3.3.

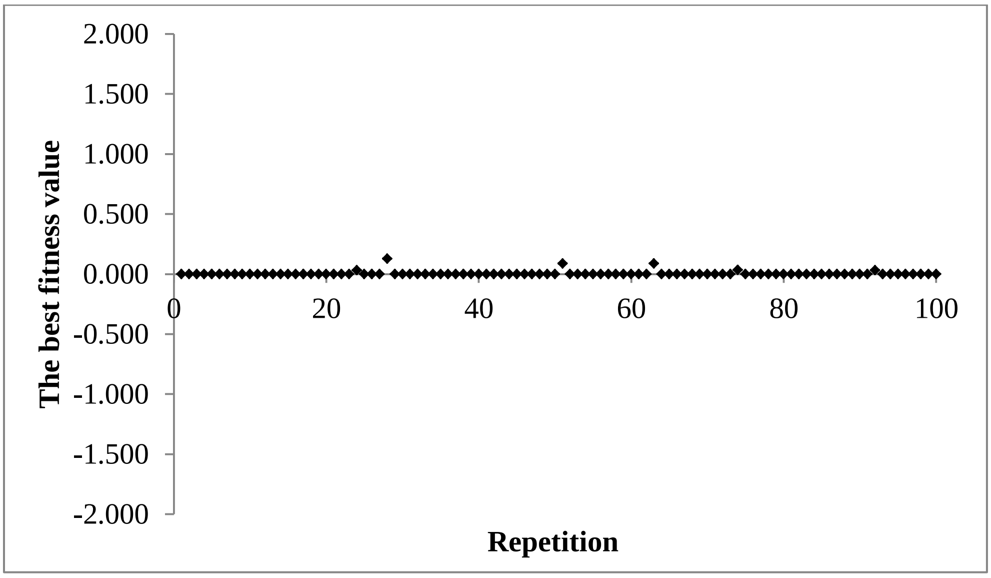
As seen in Table 3.3, the minimum and average of the objective function and of its ordinates were 0.00 for the DGA, which are also the global optimum for this special function. The range of results over 100 runs for the SGA was also higher than that of the DGA, as seen in Table 3.3. All this proof that the DGA is not only correct, it is also far superior to the SGA.

Table 3.3 The results of tested function in SGA and DGA

GA	f (x)			x			y		
	Min	Max	Ave	Min	Max	Ave	Min	Max	Ave
SGA	-1.80	1.78	0.01	-1.00	0.97	0.01	0.00	1.40	0.19
DGA	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.00



(a)



(b)

Figure 3.3 The fitness values of the algorithm of 100 repetitions for (a) SGA and (b) DGA

Setting the constraint boundary to -100 and 100 may have been too wide causing the SGA to fail on numerous. However, this does not seem to affect the DGA because the boundary was adaptively updated to obtain the true optimum space by search space reduction. The search space is then focused around the area of the optimal solution, hence improving the precision of solutions. Consequently, the SGA has been improved by search space modification using DGA, i.e. in other words, the DGA is essentially the SGA but with improved constraint boundary specification!

3.3 Simulation-optimisation reservoir model of single reservoir system

The optimisation is conducted using a single objective function. The study employed genetic algorithm (GA) and non-linear programming (NLP) linked to the problems by using Matlab and LINGO software, respectively. Matlab simulates by including the reservoir simulation into a code ‘function’ that is repeatedly called by the Matlab GA, and for the NLP, the simulation equations are embedded into the NLP constraint set. The GA generates its initial random population of decision variables by exploiting uniform random sampling within the specified ranges (as shown in Table 3.4 and 3.5). These variables are then passed as input variables to the problem simulator which evaluates the performance of the system. The performance information is passed back to the GA which evaluates the fitness of the decision variables to produce the next generation of decision variables. To ensure the final solutions are not influenced by the randomly generated initial populations, the study ran the algorithm 30 times. The results from each run are then sorted together to provide the best overall reference set.

3.3.1 The objective function

In this study, two objective functions were used for the optimisation models; minimising the sum squares of the period shortages (SS) and minimising the modified shortage index (MSI).

(1) Minimising the sum squares of the period shortages (SS), as defined in Equation (2.26) i.e.:

$$\text{Minimise } \sum_{t=1}^{N}\left(D_t - D'_t\right)^2 ,\forall\, D'_t \le D_t$$

where D_t is water demand during period, t and D'_t is water release during period, t, demand in the t^{th} period; N is the total number of time periods.

(2) Minimising the modified shortage index (MSI) of all water users i.e.:

Minimise Z (3.3)

$$z = (MSI)_p + (MSI)_d + (MSI)_i \tag{3.4}$$

where $(MSI)_p$, $(MSI)_d$ and $(MSI)_i$ are modified shortage indices, respectively, for public, downstream, and irrigation demands.

The MSI is given by Equation (2.27), i.e.: $MSI = \frac{100}{N}\sum_{t=1}^{N}\left(\frac{TS_t}{TD_t}\right)^2$

where TS_t total shortage in the t^{th} period (month); D_t is total demand in the t^{th} period; N is the total number of time periods. This index implies the effect of a deficit which is proportional to the square of the deficit ratio.

The SS objective function (Equation (2.26)) does not distinguish between the different sectors in terms of their demand amount and priority. However, the MSI objective function recognises this by making sure that shortage is weighted in proportion to the demand. In the Ubonratana case study, water allocation is prioritised in the following order: public demands, downstream requirements, and irrigation demands, respectively. However, the water demand quantity is in reverse order with public demand being the lowest. Therefore, the MSI of lowest demand, which is the highest priority, has the highest impact on the objective function. Put differently, the same amount of the deficit made at the lowest demand will cause a lower value of the objective function than is made at the highest demand.

3.3.2 The decision variables

3.3.2.1 The decision variable of rule curves

The optimisation is to determinate the monthly ordinates of the URC and LRC, as seen in Figure 3.4. The decision variables are thus the upper rule curve (URC_m) and the lower rule curve (LRC_m) for each month of the year. Consequently, the number of decision variables is 24 for the operating rule curves; decision variables 1 to 12 represent the monthly URC_m values and decision variables 13 to 24 represent the monthly LRC_m values. The existing upper ($eURC_m$) and lower ($eLRC_m$) are used to calculate the mean for setting the initial ordinates of the rule curves (mean of $eURC_m$ and $eLRC_m$). These initial estimates of ordinates of the URC and LRC for each month of the year are obtained as shown in Table 3.4. The upper constraint boundary for URC_m is the flood control rule curve ($FCRC_m$) and the lower constraint boundary for LRC_m is the minimum water level (MinWL).

Table 3.4 Boundaries of URC and LRC

Parameter	Lower bound	Upper bound	Constraint	Numbers of decision variables
LRC_m	Min.WL	Mean of $eURC_m$ and $eLRC_m$	$LRC_m \leq URC_m$	12
URC_m	Mean of $eURC_m$ and $eLRC_m$	$FCRC_m$		12

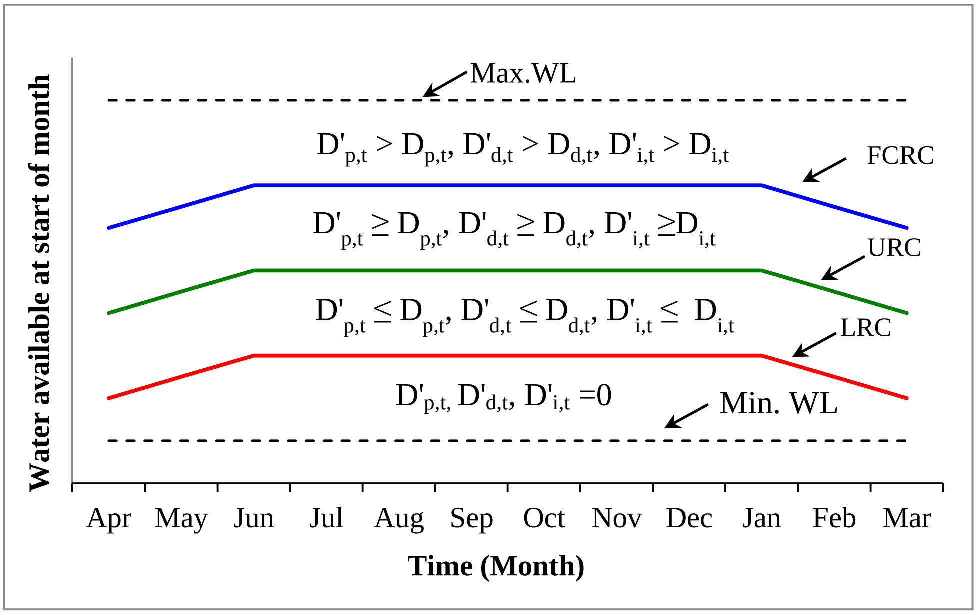
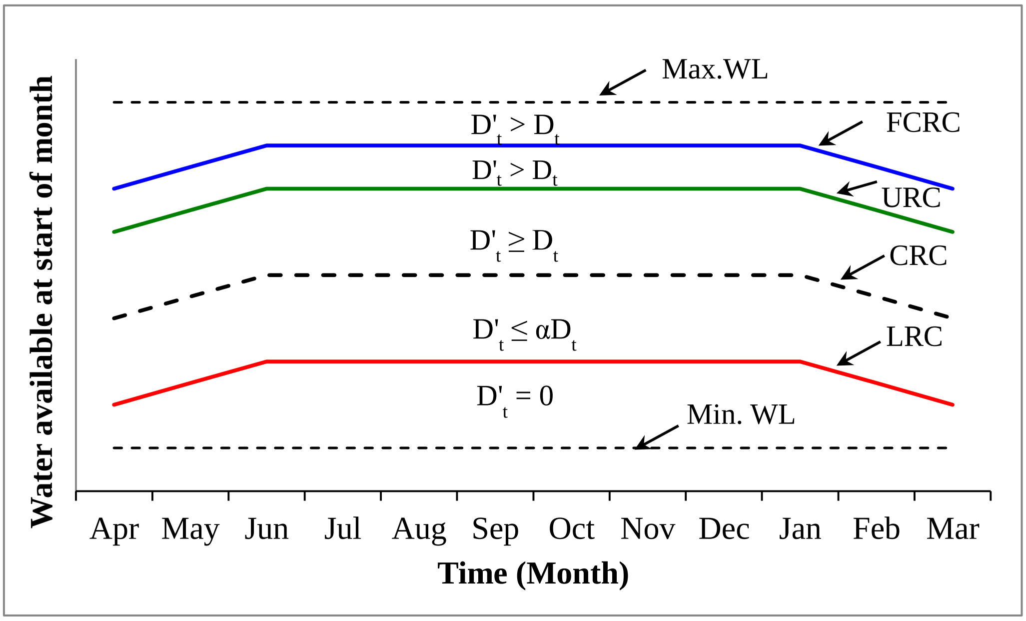


Figure 3.4 Schematic illustration of rule curves for reservoir operation

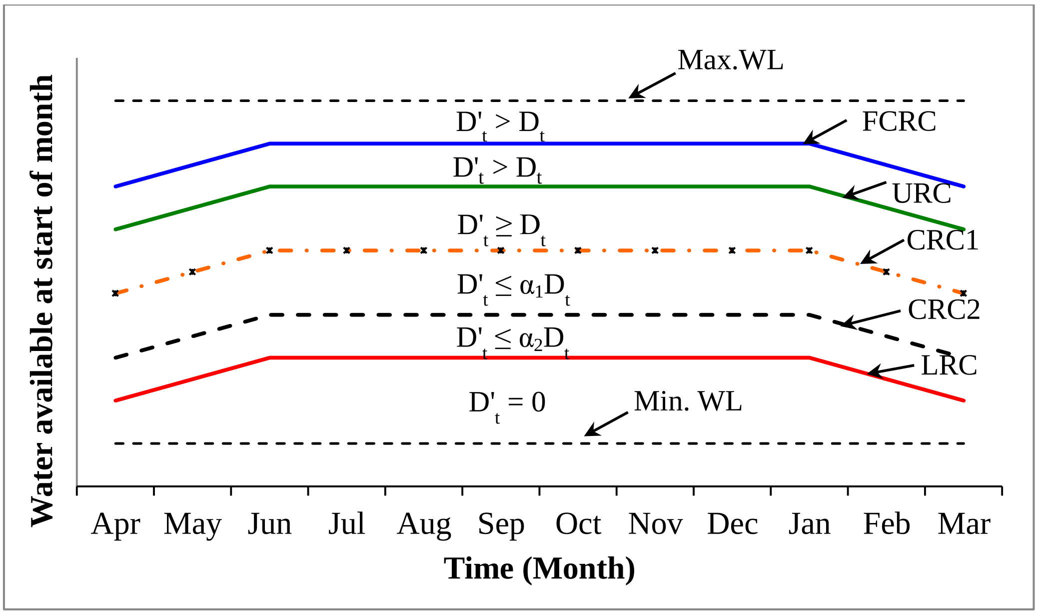
3.3.2.2 The decision variables of hedging rules

The hedging rule consists of hedging rule curves and rationing factors. The hedging rule curves are adopted to decide when to reduce water supply (i.e. the rationing trigger) and the rationing factors are used to determine the amount of water to supply. Both single stage (i.e. with one set of triggers and one rationing ratio) and two-stage hedging policies will be considered in the optimisation. Figures 3.5(a) & 3.5(b) conceptualise single-stage and two-stage hedging as developed in this study and they are developed from the no-hedging policy illustrated in Figure 3.4. The distinguishing feature between the single-stage and the two-stage is that the former has one critical rule curve (and one associated rationing ratio) while the latter has two such critical curves and ratios. Thus, in comparison with the no-hedging rule curve, normal operation in which full demand is satisfied only occurs when the reservoir storage is outside the critical storage zones.

Consequently, for the single stage hedging policy (Figure 3.5(a)), whenever the starting reservoir storage is below the critical rule curve, the water delivery is rationed by delivering only a fraction of the full demand, i.e. $D'_t = \alpha D_t$, where D'_t is the supply, D_t is the demand and α ($0 \le \alpha \le 1$) is the rationing ratio. For two-stage hedging policy (Figure 3.5(b)), the rationing is done in two levels of critical rule curves and two rationing factors to supply $\alpha_1 D_t$ and $\alpha_2 D_t$ respectively, where $0 \le \alpha_2 \le \alpha_1 \le 1$. The determination of the critical rule curves and the associated hedging factors (i.e. α, α_1 and α_2) will be achieved by GA optimisation.



(a)



(b)

Figure 3.5: Schematic illustration of hedging rules showing (a) single-stage hedging and (b) two-stage hedging

The decision variables for the reservoir operation with hedging optimisation are critical reservoir storage for each time period (CRC_m) and rationing factor (α). Thus, the numbers of decision variables are 13 and 26 for single-stage and two-stage hedging scenarios respectively, for the SS objective function (Equation (2.26)). The number of decision variables in the optimisation of the MSI objective function (Equation (2.27)) is more than the SS objective function because each water user has its own rationing factor. The numbers of decision variables are 15 and 30 for single-stage and two-stage hedging scenarios respectively for the MSI objective function. As noted previously, the initial sampling of the various decision variables will be based on the uniform density function with upper and lower boundaries. Table 3.5 shows the initial sampling of the various decision variables for the hedging rules for both objective functions.

Table 3.5 Parameters for uniform distribution sampling of decision variables

Objective function	Hedging policy	Parameter	Lower bound	Upper bound	Constraint	Numbers of decision variables
SS	Single-stage	α	0	1	$0 \le \alpha \le 1$	1
		CRC_m	LRC_m	URC_m	$LRC_m \le CRC_m \le URC_m$	12
	Two-stage	α_1, α_2	0	1	$0 \le \alpha_2 \le \alpha_1 \le 1$	2
		$CRC1_m$ $CRC2_m$	LRC_m	URC_m	$LRC_m \le CRC2_m \le CR1_m \le URC_m$	24
MSI	Single-stage	$\alpha_p, \alpha_d, \alpha_i$	0	1	$0 \le \alpha_p \le \alpha_d \le \alpha_i \le 1$	3
		CRC_m	LRC_m	URC_m	$LRC_m \le CRC_m \le URC_m$	12
	Two-stage	$\alpha_{1p}, \alpha_{1d}, \alpha_{1i}$ $\alpha_{2p}, \alpha_{2d}, \alpha_{2i}$	0	1	$0 \le \alpha_{2p} \le \alpha_{1p} \le 1$ $0 \le \alpha_{2d} \le \alpha_{1d} \le 1$ $0 \le \alpha_{2i} \le \alpha_{1i} \le 1$	6
		$CRC1_m$ $CRC2_m$	LRC_m	URC_m	$LRC_m \le CRC2_m \le CRC1_m \le URC_m$	24

3.3.3 Constraints Equations

The continuity constraint or water balance constraint (including net evaporation and ignoring other losses (L_t)) as Equation (2.7) in section 2.2.3 i.e.

$$S_{t+1} = (S_t(1 - 0.5ae_t) + Q_t - D'_t - be_t)/(1 + 0.5ae_t)$$

where S_t *and* S_{t+1} *are* the volume of storage at the beginning and end of the interval, respectively, Q_t is the inflow to the storage during the interval, et is the net evaporation in interval t (mm), *a* and *b* are coefficients which can be obtained by fitting a regression equation the available area-storage data (see Figure 2.5).

The total amount of water demand, D_t is determined by accumulating the amount of water demand of all water sectors, i.e.

$$D_t = D_{p,t} + D_{d,t} + D_{i,t} \tag{3.5}$$

The total amount of water demand releases, D'_t is determined by accumulating the amount of water releases of all water sectors, i.e.

$$D'_t = D'_{p,t} + D'_{d,t} + D'_{i,t} \tag{3.6}$$

where D_t is the total water demands during the interval which consists of public ($D_{p,t}$), downstream ($D_{d,t}$), and irrigation demands ($D_{i,t}$), D'_t the total water releases during the interval which consists of public ($D'_{p,t}$), downstream ($D'_{d,t}$), and irrigation releases ($D'_{i,t}$).

Water release is based on the amount of water available at the start of the month relative to the ordinates of the rule curves. The amount of water available, WA_t is given by:

$$WA_t = S_t + Q_t \tag{3.7}$$

The continuity constraints of the problems are that the continuity equation (see Equation 2.7) is to be satisfied for each time period. Additionally, the operation policy is given in terms of water released during period *t* according to the following possible cases of rule curves and hedging based on the water available (WA_t) during period *t*, (see Equation (3.7)).

3.3.3.1 Constraints of rule curves

The three possible cases are:

Case 1: For $WA_t \geq URC_m$ this is the excess operation case, i.e. $D'_t > D_t$.

$$D'_t = S_t + Q_t - E_t - URC_m \tag{3.8}$$

$$Y_t = D'_t - D_t \tag{3.9}$$

$$D'_{p,t} = D_{p,t}, D'_{d,t} = D_{d,t}, D'_{i,t} = D_{i,t}$$

Case 2: For $LRC_m < WA_t < URC_m$ this is the normal operation case, i.e. $D'_t \leq D_t$.

$$Y_t = 0 \tag{3.10}$$

For $\qquad WA_t - D_t \geq LRC_m, D'_t = D_t$ (3.11)

$$D'_{p,t} = D_{p,t}, D'_{d,t} = D_{d,t}, D'_{i,t} = D_{i,t}$$

For $\qquad WA_t - D_t < LRC_m, D'_t = WA_t - LRC_m$ (3.12)

$$D'_{p,t} \leq D_{p,t}, D'_{d,t} \leq D_{d,t}, D'_{i,t} \leq D_{i,t}$$

Case 3: For $WA_t \leq LRC_m$ this is the deficit operation case; $D'_t = 0$.

$$D_{p,t}' = D'_{d,t} = D'_{i,t} = 0$$

where URC_m is the upper rule curve during month *m (=1, 2, 3…,12)* of the year; LRC_m is the lower rule curve during month *m;* Y_t is the excess water released during period *t*. In general, $t = 12(y-1) + m$ for years $y = 1, 2, 3…., n$, where n is the number of years in the data record.

3.3.3.2 Constraints of hedging rules

(i) Single-stage hedging

The four possible cases are:

Case 1: For $WA_t \geq URC_m$ this is the excess operation case, i.e. $D'_t > D_t$.

$$D'_t = S_t + Q_t - E_t - URC_m \quad (3.13)$$

$$Y_t = D'_t - D_t \quad (3.14)$$

Case 2: For $URC_m \geq WA_t > CR_m$ this is the normal operation case, i.e. $D'_t \leq D_t$.

$$Y_t = 0 \quad (3.15)$$

For $\quad WA_t - D_t \geq LRC_m, D'_t = D_t \quad$ (3.16)

For $\quad WA_t - D_t < LRC_m, D'_t = WA_t - LRC_m \quad$ (3.17)

Case 3: For $CRC_m \geq WA_t > LRC_m$ this is the deficit operation case according to the hedging factor, i.e. $D'_t < D_t$.

$$Y_t = 0 \quad (3.18)$$

For $\quad WA_t - D_t \geq LRC_m$,

In case of the SS objective function, $D'_t = \alpha D_t \quad$ (3.19)

In case of the MSI objective function,

$$D'_{p,t} = \alpha_p D_{p,t}, D'_{d,t} = \alpha_d D_{d,t}, D'_{i,t} = \alpha_i D_{i,t} \quad (3.20)$$

For $\quad WA_t - D_t < LRC_m, D'_t = WA_t - LRC_m \quad$ (3.21)

Case 4: For $WA_t \leq LRC_m$ this is the deficit operation case; $D'_t = 0$.

where α is the rationing factor for single-stage policy; α_p, α_d and α_i are the rationing factors of public, downstream and irrigation demands, respectively; CRC_t is the critical storage at time *t* (single-stage policy) as previously defined in Table 3.4.

(ii) Two-stage hedging

The five possible cases are:

Case 1: For $WA_t \geq URC_m$ this is the excess operation case, i.e. $D'_t > D_t$;

$$D'_t = S_t + Q_t - E_t - URC_m \tag{3.22}$$

$$Y_t = D'_t - D_t \tag{3.23}$$

Case 2: For $URC_m \geq WA_t > CRC1_m$ this is the normal operation case i.e. $D'_t \leq D_t$;

$$Y_t = 0 \tag{3.24}$$

For $\quad WA_t - D_t \geq LRC_m, D'_t = D_t$ (3.25)

For $\quad WA_t - D_t < LRC_m, D'_t = WA_t - LRC_m$ (3.26)

Case 3: For $CRC1_m \geq WA_t > CRC2_m$ this is the deficit operation case according to the first hedging factor, i.e. $D'_t < D_t$;

$$Y_t = 0 \tag{3.27}$$

For $\quad WA_t - D_t \geq LRC_m,$

In case of the SS objective function, $D'_t = \alpha_1 D_t$ (3.28)

In case of the MSI objective function,

$$D'_{p,t} = \alpha_{1p} D_{p,t}, D'_{d,t} = \alpha_{1d} D_{d,t}, D'_{i,t} = \alpha_{1i} D_{i,t} \tag{3.29}$$

For $\quad WA_t - D_t < LRC_m, D'_t = WA_t - LRC_m \quad$ (3.30)

Case 4: For $CRC2_m \geq WA_t > LRC_m$ this is the deficit operation case according to the second hedging factor i.e. $D'_t < D_t$;

$$Y_t = 0 \tag{3.31}$$

For $\quad WA_t - D_t \geq LRC_m$,

In case of the SS objective function, $D'_t = \alpha_2 D_t \quad$ (3.32)

In case of the MSI objective function,

$$D'_{p,t} = \alpha_{2p} D_{p,t}, D'_{d,t} = \alpha_{2d} D_{d,t}, D'_{i,t} = \alpha_{2i} D_{i,t} \tag{3.33}$$

For $\quad WA_t - D_t < LRC_m, D'_t = WA_t - LRC_m \quad$ (3.34)

Case 5: For $WA_t \leq LRC_m$ this is the deficit operation case, i.e. $D'_t = 0$.

where α_1 and α_2 are the rationing factors of the first and second stage , respectively, for 2-stage policy; α_{1p}, α_{1d} and α_{1i} are the rationing factors of the first stage of public, downstream and irrigation demands, respectively; α_{2p}, α_{2d} and α_{2i} are the rationing factors of the second stage of public, downstream and irrigation demands, respectively; $CRC1_t$ is the critical storage at t (first stage, 2-stage policy); $CRC2_t$ is the critical storage at t (second stage, 2-stage policy) as previously defined in Table 3.4.

3.4 Reservoir performance evaluation

Full details about the reservoir performance indices commonly used in water resources evaluation were given in section 2.3 and will not be repeated here for obvious reasons. However, it is sufficient to state here that the indices were not included as part of the objective function but were evaluated following the completion of the optimisation. Although several equations of resilience, vulnerability and sustainability indices were reviewed in section 2.3, Equation (2.10), (2.18) and (2.21) are used to determine the resilience, vulnerability and sustainability, respectively, in this study.

3.5 Reservoir inflow forecasting model based on artificial neural network method (ANN)

As discussed earlier in the literature review, this study used ANN for the inflow forecasting because ANN has ability for mapping most non-linear models and capturing the complex function relationship.

3.5.1 Artificial neural network modelling

The neural networks models developed in this study were trained in MATLAB Programming language according to the following steps.

1. Data pre-processing: the data are normalised using the mean and standard deviation, the Equation (2.57) described in section 2.7.3.3 in order to improve the performance of the model.

2. Creating a feed forward back-propagation network. The architecture is selected, that is, the number of nodes in the input layer, hidden layer and output layer. For a given problem, the number of nodes in the output layer is fixed by the problem, e.g. in the current work, it is the one-month ahead inflow forecast. The input nodes are determined by the factors known to affect the output variables and this has been achieved through an examination of the autocorrelation (act) partial correlation (pact) and cross-correlation (ccf) function as suggested by Sudheer et al. (2002). Choosing the number of hidden neurons is presented later in the next section.

3. Choosing training and learning function: training and learning function are mathematical procedures used to automatically adjust the network weights and biases. The MATLAB includes several training function but the Levenberg-Marguardt back-propagation (Trainlm) with early-stopping rule (ESR) was used. The ESR was used for the ANN training and for this the 360 months (April1982-March2012) of data were split into three (90:5:5) for training, validation and testing, respectively.

4. Choosing the performance function to calculate and monitor network efficiency during training. MSE is used to measure the network error in this study.

5. Selecting transfer functions: In this study the tangent sigmoid transfer function is used to transfer the values of the input layer nodes to the hidden layer nodes, while the linear transfer function is employed to transfer the values from the hidden layer to the output layer. The linear function in the output layer was chosen because, as explained by Yonaba et al. (2010), that linear transfers function is suitable for the output layer, while usage of a nonlinear transfer function in the output layer failed in improving performance values.

6. Post-processing: this can be achieved by examining the predictive power of the model with testing data set that has not been used during training.

7. Presenting the results of training, validation and testing in figures and tables

3.5.2 Model development

3.5.2.1 The number of hidden neurons selection

Selecting the number of hidden nodes is a difficult task to build the ANN model; there is no net theory yet to select the appropriate number of neurons in the hidden layer (Zhang et al, 2009). Therefore, experimenting with a trial and error measure is recommended as the best strategy by Shamseldin (1997) and described by Adeloye and De-Munari (2006), and is used in this study. The trial and error method is used to determine the nodes number in a single hidden layer of ANN in this study. Eberhart and Dobbins (1990) suggested that by using the trial and error method the number of hidden neurons should start at least to be equal to half the number of input neurons. To avoid the poor approximation caused by too small neurons and the over-fitting problem caused by too many neurons, the number of hidden neurons was varied between 1 and 35 and based on the correlation coefficient (R) criterion recommendation by Coulibaly et al. (2000).

3.5.2.2 Evaluation of performance

Once a model structure has been chosen and the network trained, the selected model needs to be evaluated. In practice, the accuracy of a model is determined by the goodness of fit between outputs of the model and the target or observed values. Hence, some validation tests need to be considered. Generally, the accuracy of a model must be evaluated for three sets of data samples. These data sets are: training data that express the effectiveness of learning, validation data set that measure the generalisation capability of the network. In this work, the following evaluation criteria have been considered.

1. The mean square error (MSE) which is defined as:

$$MSE = \frac{\sum_{1}^{N}(y_{sim} - y_{obs})^2}{N} \tag{3.35}$$

2. The correlation coefficient (R) measures the similarity of the shapes of the observed and predicted time series and ranges between -1 and 1; the absolute value of the correlation coefficient for perfect prediction is unity.

$$R = \frac{\sum y_{sim}y_{obs} - \frac{\sum y_{sim}\sum y_{obs}}{N}}{\sqrt{(\sum y_{sim} - \frac{(\sum y_{sim})^2}{N})(\sum y_{obs}^2 - \frac{(\sum y_{obs})^2}{N})}} \tag{3.36}$$

3. The Nash-Sutcliffe efficiency, E, proposed by Nash and Sutcliffe (1970) is defined as one minus the sum of the absolute squared difference between the predicted and observed values normalised by the variance of the observed values during the period under investigation. The range of E lies between 1 (perfect fit) and $-\infty$.

$$E = 1 - \frac{\sum_{i=1}^{N}(y_{obs} - y_{sim})^2}{\sum_{i=1}^{N}(y_{sim} - \bar{y}_{obs})^2} \tag{3.37}$$

where y_{sim} is the predicted output; y_{obs} is the observed output or target and N is the number of data points.

3.5.3 Evaluating the effect of forecasting inflow on reservoir operation

The simulation model is based on the situation of water available. Peng et al. (2015) defined the two basic situations of water available in operating rules. First, it is defined as a function of reservoir storage plus inflow. Second, it is a function of the reservoir storage only. In case the inflow information is not available or the inflow forecasting accuracy is poor, this second condition is often applied for water supply reservoir simulation. Depending on which scenario is assumed, the reservoir performance will be affected. However, since most reservoir operation activities are associated with inflow forecasting, it will be important to test how the inflow forecasting will affect the performance of the reservoir. Such a test will be more informative of the forecasting skill of the ANN than the use of the statistical measures presented as follows.

As discussed earlier, reservoir operation concerns taking decisions on water release from a reservoir based on the amount of water available vis-á-vis the demand placed on the system. The available water is the sum of starting period storage and the inflow expected during the period as defined in Equation 3.7, defined as follows,

$$WA_t = S_t + Q_t$$

and assumes that the inflow is known at the start of the month when making the release decision. In practice, however, this is not the case and assumptions about the size of the anticipated inflow must be made. If the actual inflow turns out to be exactly the same as the assumed inflow, then the end of period storage will be exactly as given by Equation 2.7, i.e.:

$$S_{t+1} = (S_t(1-0.5ae_t) + Q_t - D'_t - be_t)/(1+0.5ae_t)$$

If, however, there is a discrepancy, the actual end of period storage will be different from Equation 2.7. Let the actual end-of-period storage be $S_{end,t}$, the relationships between this and S_{t+1} for each of the assumed inflow knowledge assumptions become:

(1) Type A: $WA_t = S_t + Q_t$ and $S_{end,t} = S_{t+1}$

(2) Type F: $WA_t = S_t + Q'_t$ and $S_{end,t} = S_{t+1} + Q_t - Q'_t$

(3) Type M: $WA_t = S_t + \overline{Q}_t$ and $S_{end,t} = S_{t+1} + Q_t - \overline{Q}_t$

(4) Type N: $WA_t = S_t$ and $S_{end,t} = S_{t+1} + Q_t$

where Q_t is the observed (correct) inflow during time t, Q'_t is the corresponding forecast inflow, $\overline{Q}_t$ is the historic mean flow for the month of time t, and $S_{end,t}$ is the adjusted end-of-period storage. The monthly inflow forecasts are used to evaluate three operating policies for the Ubonratana reservoir: (1) the optimised rule curves, (2) one-stage hedging and (3) two-stage hedging; its results are shown in chapter 5.

3.6 Computer software

3.6.1 MATLAB software

The developed models were implemented using MATLAB R2014 programming language with genetic algorithm and neural network toolboxes. The dynamic genetic algorithm was built and modified the code of GA toolbox. The MATLAB programming language was chosen for model development because it provides comprehensive support for design, implementation, and simulation of the models rapidly. Their consistent methodology and modular organisation provide a flexible framework for experimentation, and simplify customisation. The work models were performed using the available advice in the documentation of the software's user guide and in the literature.

3.6.2 LINGO software

LINGO has been widely used in water resources problems and is considered to be a simple and robust tool for solving linear (Ziaei et al., 2012) and nonlinear (Jothiprakash and Arunkumar, 2004) optimisation problems. LINGO software was designed by LINDO Systems, Inc. Company in order to facilitating optimisation problems in university, industry and business (LINDO, 2004). In this study, the optimisation using NLP has applied the LINGO15 model. LINGO is one of the most popular languages to support the NLP formulation. One of the useful features of LINGO is that it does not require a user to define the solver (e.g. linear or nonlinear), because LINGO can read the given formulation and automatically selects the appropriate solver. With LINGO, the input data can be directly read from databases which are called directly from Excel spread sheets. Finally, the solution information or the results can be sent back into the database in the Excel spreadsheet.

3.7 Summary

This chapter presents the methodology applied in this study. It starts with a methodology flow diagram. An overview of computer softwares used in this study is also presented briefly. The procedure of the new dynamic genetic algorithm approach (DGA) is described. The decision variables, objective functions and constraints of optimisation for rule curves and hedging rules are presented. The GA parameters used are defined in the chapter. To benchmark the performance of DGA and SGA, the results of optimisation of DGA and SGA using the Scaffer'F7 were demonstrated in section 3.3.2.2. The inflow forecasting process and the performance evaluation criteria used to assess the forecasting models are presented. The chapter ends with the evaluating the effect of inflow forecasting on the reservoir operation to assess the developed reservoir models. Thus the previous chapters have covered all the basic of the methodology and the reservoir performance evaluation. The next chapter will present the case study and data collection.

Chapter 4 Study Area

4.1 General information

Thailand is located in the tropical area between latitudes 5° 37′ N to 20° 27′ N and longitudes 97° 22′ E to 105° 37′ E. The total area of the country is 513,115 square kilometres or around 200,000 square miles (Thai Meteorological Department, 2012). Thailand is located in Southeast Asia and bordered in the north by the Lao People's Democratic Republic (Lao PDR), in the east by Lao PDR and Cambodia, in the south by the Gulf of Thailand and Malaysia, and in the west by the Andaman Sea and the Union of Myanmar, as seen in Figure 4.1. As of 2014, the estimated population was about 67 million, with a growth rate of 0.3 percent per year (Worldometers, 2015). The urban population was estimated at about 35% of the population, with a high concentration in the capital Bangkok and the regional centres (Worldometers, 2015). According to the climate pattern and meteorological conditions, Thailand is divided into 5 parts i.e. Northern, Northeastern, Central, Eastern and Southern Parts. Most of Thailand has a climate determined by three seasons (i.e. summer, rainy and winter) though the southern peninsular region of Thailand has only two (i.e. summer and rainy). Most areas of the northern part are hilly and mountainous, and form the location for the source of several important rivers. The northeastern region is naturally a high level plain, referred to as the northeast plateau. In the southern part, temperatures are generally mild throughout the year because of the maritime characteristics of this region. Because of the length of the rainy season (around 8 months) in the southern part, the average annual rainfall of this region is around 2,400 mm which is much higher than the average annual rainfall of the central and northern regions (Thai Meteorological Department, 2012).

4.1.1 Background of climatic conditions

The climate of Thailand is under the influence of monsoon winds of seasonal character i.e. southwest monsoon and northeast monsoon. The onset of monsoons varies to some extent. Southwest monsoon usually starts in mid-May and ends in mid-October while northeast monsoon normally starts in mid-October and ends in mid-February. The southwest monsoon brings a stream of warm moist air from the Indian Ocean towards Thailand causing abundant rain over the country, especially the windward side of the mountains. The northeast monsoon brings the cold and dry air from the anticyclone in China mainland over major parts of Thailand, especially the Northern and Northeastern Parts. According to a general annual rainfall pattern, most areas of the country receive 1,200- 1,600 mm (Thai Meteorological Department, 2012).

The approximate runoff is 213,500 million cubic meters per year, which is 30% of the total precipitation, and gives annual runoff capita of 3,285 million cubic meters. Rainfall is very seasonal in Thailand and this produces significant seasonality in the runoff. In general, 86% of the total runoff occurs in the rainy season (RID, 2009).

The Ubonratana reservoir is located in the Northeastern Thailand (Figure 4.1). The climate in this region is normally divided into 3 seasons: summer or pre-monsoon season (mid-February to mid-May), rainy or southwest monsoon season (mid-May to mid-October) and winter or northeast monsoon season (mid-October to mid-February). For cultivation purposes, the crop growing periods consist of the wet period (May-October) and dry period (November-April).

4.1.2 Irrigation

The agricultural area in Thailand is approximately 209 x10^3 km^2, but only 96 x10^3 km^2 is the irrigation area (Haii Wiki, 2010). Because of the enhanced water supply for irrigation, the agriculturists in the irrigation area have an average income which is more than three times that of agriculturists who live in the non-irrigation area (Pongsatananukul and Sirikanchanarat, 2011). Moreover, Thailand is the world's largest exporter of rice i.e. approximately 30% of the world market (Sachchamarga and Williams, 2004). More than 50% of Thailand agricultural areas are developed as rice paddies. This is because rice is a major crop in Thailand, accounting for approximately 30% of the total value of agricultural production and 12% of the total value of agricultural exports (Sachchamarga and Williams, 2004). Rubber, which is one of the major exports, is grown on the peninsula in the southeast Thailand. The cultivation area of rubber is about 12% of the total agricultural area. Sugarcane and cassava (tapioca) are also major exports grown in the eastern and northeastern Thailand, with each crop having a cultivation area about 5% of the total agricultural area. Thailand provided about 95% of the world's cassava exports in 1985 (Curran and Cooke, 2008).

There are four types of water resources for a rice paddy: (1) surface water irrigation, (2) groundwater irrigation, (3) rain-fed lowland, and (4) rain-fed upland ecosystem (Sachchamarga and Williams, 2004). The main water resources for most of the rice and other agricultural products come from rainfall, which is highly variable in both its magnitude and timing. Indeed, the rainfall in Thailand is dominated by the monsoon occurring during July-September. Therefore, the government has invested in irrigation projects involving large reservoirs to regulate the high variability of water availability from rainfall and to reduce the possibility of water scarcity that farmers frequently face.

4.2 Chi River basin

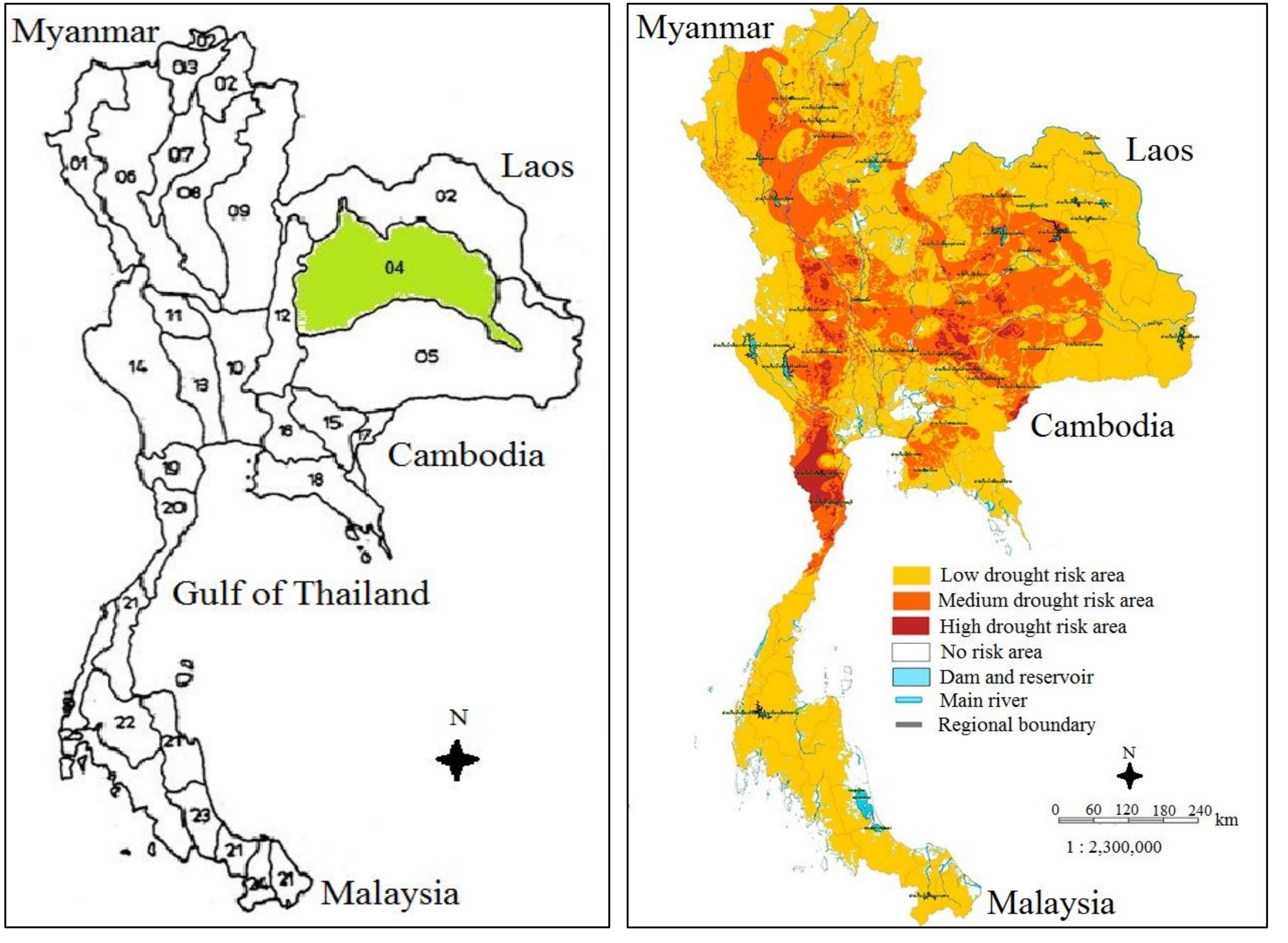
Thailand is divided into 25 river basins (Figure 4.1(a)) and the Chi river basin is identified as basin 4, with a catchment area of about 49477 km^2. General information about all 25 river basins is summarised in Table 4.1. All these river basins are important water resources for municipal, industrial and agriculture purposes in Thailand. Figure 4.1(b) illustrates the drought risk areas in Thailand and shows that the majority of the Chi river basin in northeastern Thailand is a medium drought risk area. Drought is one of the most serious water resource problems in northeastern Thailand due to the uncertainty in monsoon rainfall patterns. Increasing water demands due to increases in population and acreage cultivated for food production, in combination with the temporal and spatial variability in river flow and rainfall, make irrigation inevitable.

In the north-eastern part of Thailand, most of the people live in rural areas and their main income is agriculture, which is the main source of employment and livelihood. Therefore, water for irrigation purposes is important for farmers. The multi-purpose Ubonratana reservoir is the case study reservoir. The Ubonratana Reservoir is the largest reservoir in Chi river basin and it is the main water resources for irrigation in the region. Annual average rainfall in this region is about 1040 mm in around 104 rainy days (Khon Kaen Meteorological Station, 2010). The monthly rainfall data at Nong wai of 372 months (1981-2012) was provided by Royal Irrigation Department (RID), as seen in Figure 4.4 and Table A7 in appendix A. The average daily temperature range is 19-37^{o}C.

The dam and its reservoir have made it possible to extend the rice cultivation period in the area of Nong wai irrigation project, from one crop per year to continuous rice cultivation. The total planted area in Khon Kaen has also increased by about 22% in the past 30 years (Kawasaki and Herath, 2011). The Ubonratana Reservoir thus plays a key role in the social-economic well-being and income of the people in the region. As a result, the reservoir policies can affect the economy of the province and people who live downstream of this irrigation system. To achieve this, better operational practises within the context of the prevailing hydrology are required.

4.3 Reservoir characteristics

The dam is located on the Pong River at Phong Neap, Ubonratana district in Khon Kaen province, between latitudes 16° and 17°30' N and longitudes 101°15" and 102°45" E. The catchment area at the dam site is 12000 km^2. The reservoir was completed in 1966 and started operation in 1970. The reservoir has a storage capacity of 2,431Mm^3. The dam height is 36 m, with a length of 885 m (including the 100 m spillway) and a width of 6 m at the top (EGAT, 2002). The minimum storage volume is 581 Mm^3 for generating hydropower; the dead storage is 120 Mm^3 (EGAT, 2002).



(a) (b)

Figure 4.1 Map of Thailand showing (a) the 25 river basins (www.fao.org) and (b) the drought risk area (www.gfdrr.org)

Table 4.1 General information on the 25 river basins in Thailand (Ti and Facon, 2001)

Basin No.	Name of river basin	Catchment area	Average runoff (10^6 m^3)	Storage capacity (10^6 m^3)	Irrigation area (rai)	water requirement (10^6 m^3/year)				
						Domestic consumption	Tourism industry	Ecological balance	Irrigation / Agriculture	Hydropower
1	Salawin	17920	8571	24.00	188948.00	11.96	4.46	1027.80	616.93	-
2	Mekong	57422	19362	1551.00	1692333.00	132.57	1.98	1145.60	4323.30	-
3	Kok	7895	5279	30.00	520767.00	14.90	0.43	680.00	401.39	-
4	Chi	49477	8752	4246.00	1863173.00	195.17	49.62	573.33	3052.80	2156.00
5	Mun	69700	26655	4255.00	1819785.00	337.88	94.30	956.63	2628.80	591.30
6	Ping	33898	7965	14107.00	1942927.00	75.26	1.00	457.27	2428.20	3623.00
7	Wang	10791	1104	197.00	472350.00	20.21	1.00	48.00	487.42	45.00
8	Yom	23616	3117	98.00	994205.00	53.87	0.08	315.36	859.13	-
9	Nan	34330	9158	9619.00	1780637.00	66.29	0.32	315.36	2870.80	2583.00
10	Chao Phraya	20125	22015	33.00	5731375.00	1594.40	646.05	1250.00	8768.50	-
11	Sakaekrang	5191	1297	162.00	436410.00	8.62	-	3.35	878.75	-
12	Pasak	16292	2820	124.00	661120.00	72.32	23.28	158.00	927.38	-
13	Tha Chin	13682	22300	416.00	2385259.00	94.94	310.25	1000.00	4292.10	-
14	Mae Klong	30837	7973	26690.00	3400000.00	20.34	-	1577.00	4323.30	4670.00
15	Prachinburi	10481	5192	57.00	733862.00	8.08	2.78	377.00	838.32	-
16	Bang Pakong	7978	3713	74.00	1353263.00	14.18	9.05	946.00	2243.60	1.94
17	Tonle Sap	4150	6266	96.00	123720.00	12.60	-	9.80	197.00	-
18	Pen. East Coast	13830	11115	565.00	427000.00	129.10	83.50	74.70	578.46	79.00
19	Phetchaburi	5603	1400	750.00	562688.00	14.30	2.90	67.00	1110.00	693.00
20	Pen. West Coast	6745	1420	537.00	327015.00	18.00	2.97	39.10	1383.00	-
21	Southeast Coast	26353	23270	5.00	1780481.00	56.40	8.70	161.70	1129.10	2577.00
22	Tapi	12225	12513	5865.00	245970.00	25.90	10.00	3085.20	144.60	2596.00
23	Songkhla Lake	8495	4896	28.00	905550.00	56.45	37.50	312.00	2994.70	-
24	Pattani	3858	2738	1420.00	337878.00	31.20	2.44	670.80	441.11	1152.00
25	Southwest Coast	21172	25540	20.00	339273.00	53.20	18.90	74.80	253.00	-
	TOTAL	**512066**	**244431**	**70969.00**	**31025989.00**	**3118.14**	**1311.51**	**15325.80**	**48171.69**	**20767.24**

NB: 6.25 rai = 1 ha

4.4 Water demands in the Ubonratana reservoir

Purposes served by the reservoir are municipal water demand, industrial demand, downstream water requirement, other agriculture requirements downstream and irrigation as shown in the schematic diagram of the reservoir and the various diversions (Figure 2.1). For planning purposes in the Ubonratana reservoir, the municipal and industrial water demands are considered as the highest priority. The minimum flow requirements and other agriculture requirements downstream are considered the second priority. The demand for the Nong wai irrigation project is the last priority. All the water deliveries first pass through the turbines for power generation before being allocated to the other uses in the order mentioned in a winner-takes-all fashion. In other words, an attempt is first made to satisfy the domestic water demand in full if possible after which, if there is water left, attention turns to the second priority user and so on.

Gross water requirements for the period of April 1980-March 2012 (384 months) were 30,140 Mm^3, i.e. average annual public demands of 11 Mm^3 (municipal and industrial), average annual downstream requirements of 224 Mm^3 and an average annual irrigation demand of 706 Mm^3. The mean monthly water requirements are shown in Table 4.2. The monthly municipal, industrial, irrigation, downstream and other demands from April 1980 to March 2012 are shown in Table A1, A2, A3, A4 and A5 in Appendix A, respectively.

Table 4.2 The average monthly water demands, rainfall and inflow

Month	Water demand (Mm^3)					Rainfall (mm)	Inflow (Mm^3)
	Municipal	Industrial	Irrigation	Downstream	Other		
Apr	0.491	0.418	53.376	12.281	7.515	76.781	36.310
May	0.491	0.429	31.731	12.691	3.190	130.400	106.690
Jun	0.492	0.419	54.652	12.563	2.976	126.748	197.324
Jul	0.529	0.434	79.240	12.981	7.771	125.190	177.815
Aug	0.502	0.436	74.349	12.981	5.125	185.486	313.034
Sep	0.483	0.422	72.892	12.563	3.406	205.786	841.693
Oct	0.508	0.437	76.226	12.981	6.564	84.433	664.283
Nov	0.473	0.422	28.903	12.563	7.988	9.819	152.259
Dec	0.496	0.418	36.442	12.981	4.080	5.567	28.802
Jan	0.514	0.466	69.903	12.981	5.737	2.381	21.187
Feb	0.465	0.423	62.183	11.725	9.527	14.938	20.340
Mar	0.524	0.468	66.446	12.981	8.217	31.357	26.928

(1) Irrigation Demand

Nong Wai irrigation project covers the area of 415 km^2 or 259,400 rai (EGAT, 2002). The project was begun in 1977. Water is supplied in the rainy season for rice cultivation and the dry season for rice and other crops cultivation (e.g. cassava, corn, and sugar cane). The highest water demand in the dry season (Dec - May) for 240 km^2 of irrigation area is about 588 Mm^3 (year 2010). The highest water demand in the rainy season (June - Nov) for 415 km^2 of irrigation area is about 593 Mm^3 (year 1992). The monthly irrigation demand for Nong wai irrigation project from April 1980 to March 2012 is shown in Table A3 in Appendix A.

(2) Ecosystem

Minimum stream flow required for maintaining river ecosystem is 4 m^3/s or 0.35 Mm^3/day, downstream of the Ubonratana reservoir (EGAT, 2002). As noted earlier, instream requirements come after domestic water supply in the scheme of priority for allocating the available water, and the release of this amount (4 m^3/s) of water takes place irrespective of the flow situation downstream of the dam. While such a release might be required during low flow conditions, its release to an already full river cannot be justified and the water is better used for other low-priority purposes in that situation. In any case, the basis of the constant demand is unknown and the use of a constant instream-flow demand is not in tune with modern methods of ensuring the ecological health of the river (Acreman and Dunbar, 2004). However, it has been adopted for the study because it is currently the practice at Ubonratana but it will be important for better estimates of the environmental flow that accounts for the ecosystem services sustainability in the basin to be produced. The monthly in-stream requirement from April 1980 to March 2012 is shown in Table A4 in Appendix A.

(3) Hydropower Generation

The Ubonratana Reservoir is constructed for protection from flood during the rainy season and from drought in the dry season. Hydropower is generated when the water deliveries first pass through the turbines before being allocated to respective needs. Therefore, the amount of electricity production generated by hydropower can vary widely depending on water releases from the reservoir. The minimum water level for hydropower generation is 175 mamsl or 581 Mm3. In practice, generating hydropower is not the priority of the dam, so the reservoir manager allows the storage level to be lower than this level during drought and discharges of water are strictly prioritised according to the most critical water demands. The generation capacity of three generators is 25.2 MW. It houses three sets of vertical shaft Kaplan turbines, each of 8.75 MW capacity and three sets of generators each of 8.4 MW capacity. The hydropower plant produces an average of 65 million kWh (kilowatt-hours) per year and the minimum generation is 0.01 MW (EGAT, 2002).

4.5 Data collection

Irrigation is the responsibility of the Royal Irrigation Department (RID) of Nong wai and they provide EGAT with estimates of the irrigation water requirements and water allocation plan for the Nong Wai project. The monthly irrigation water demand data1980-2012 (384 months) data were provided by the RID. Gauging of the tributary at Nong Wai weir started in 2002; however, EGAT had estimated the pre-2002 tributary flows using a rainfall–runoff approach in combination with a water balance accounting of the record of releases and abstractions from the Ubonratana reservoir. Thus, monthly runoff data spanning 1970-2012 were also available. The mean monthly rainfall at Nongwai of 1981-2012 were provided by the RID is shown in Table A6, appendix A.

The mean monthly rainfall at Ubonratana of 1988-2008 and the mean monthly inflow data of 1970-2012 are also shown in Table 4.2. The average monthly rainfall at Ubonratana reservoir distribution is shown in Figure 4.2(c), which also contains the monthly mean evaporation rates. The mean monthly rainfall data at Ubonratana reservoir of 21 years (1988-2008) were provided by RID, as seen in Table 4.2 and Table A9 in appendix A. Because of the shortness of the rainfall and evaporation data relative to the reservoir inflow data, only the mean monthly values of both the evaporation and rainfall were used to calculate mean values of the net evaporation for the reservoir simulations. As previously found out by Fennessey (1995), using mean values of the net evaporation in reservoir simulations produced no significant difference from using time series data of net evaporation. The reservoir monthly inflow data of 1970-2012 (504 months) are shown in Figure 4.4, and the average monthly evaporation data provided by

EGAT, the dam's operators, are shown in Tables A8 and A9, respectively, in appendix A. The average annual inflow is 2619 Mm^3 which includes the runoff and direct rainfall on the reservoir surface.

The elevation–area–storage relationship was previously shown in Figure 2.2 (section 2.2) and Table A7 in appendix A. This was surveyed in 2002 but was assumed to be valid for the entire simulation period. As noted previously, Figure 2.2 is needed for incorporating evaporation loss in the simulation. The area–storage relationship is shown in Figure 4.2(b). As noted previously, Figure 4.2(b) was used to determine the coefficient of a and b, for incorporating evaporation loss in the water balance equation in Equation (3.7).

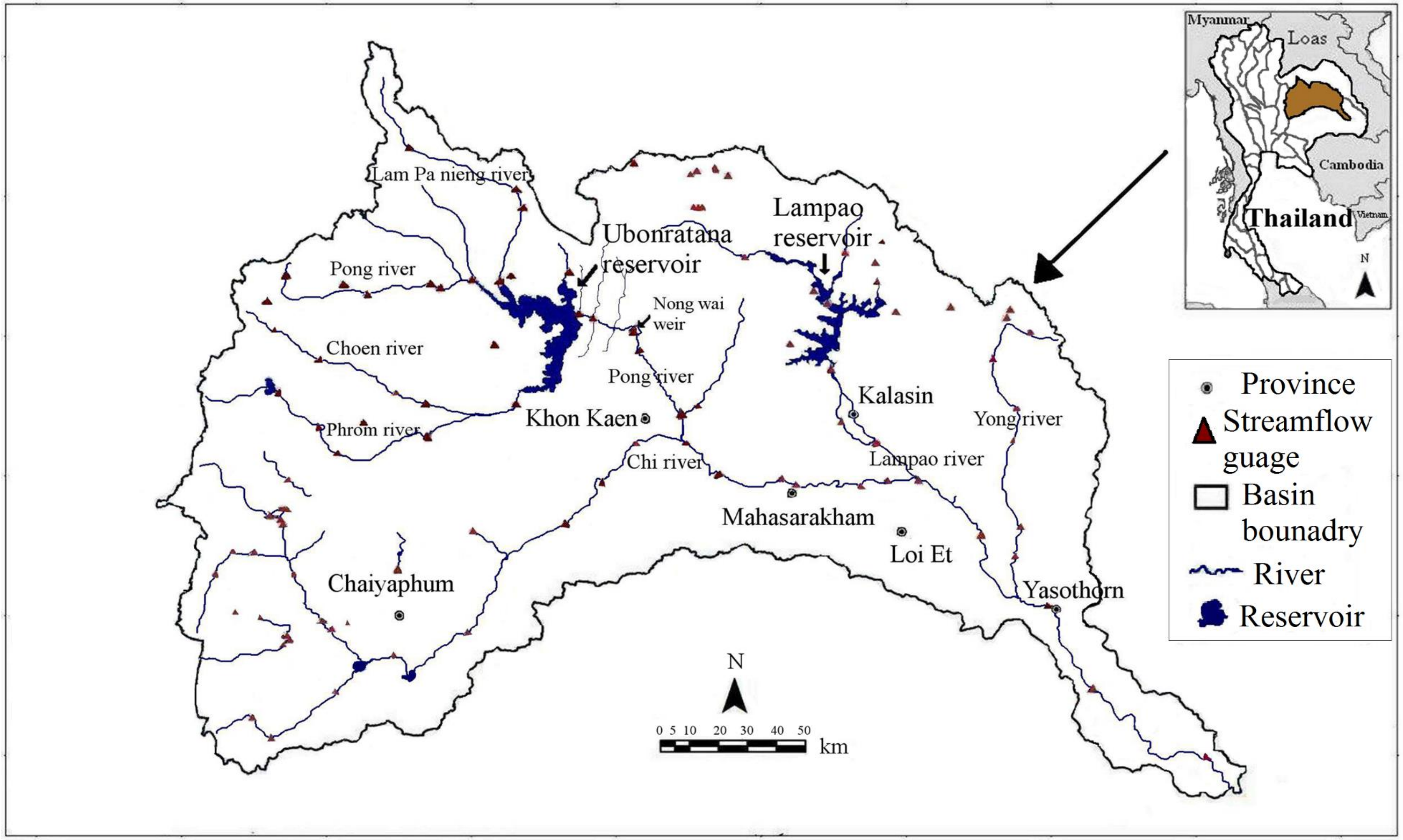
4.6 The Ubonratana reservoir operation

The single, multi-purpose reservoir has been operated for a long time using rule curves developed by the Electricity Generating Authority of Thailand (EGAT), the dam operators. Figure 4.5 shows the pre-2002 rule curves at Ubonratana, which can be used to illustrate how rule curves help in guiding reservoir operation. In 2002, because of a severe flood that devastated the region (as seen in Figure 4.3), a revised set of Ubonratana rule curves was derived, essentially involving the lowering of the upper rule curve of the existing rules (pre-2002 policy) to accommodate more flood water, this is called the post-2002 rule curves (as seen in Figure 4.6). While this resulted in reducing the flooding impacts, it worsened the ability of the reservoir to meet the water demand needs, especially during extremely low flow periods.

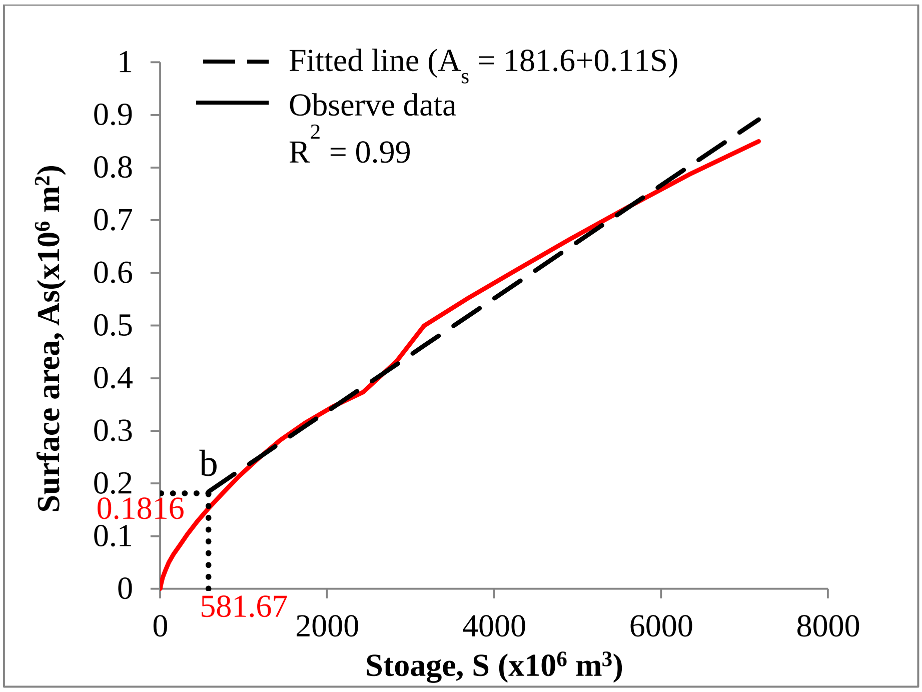
To improve the situation with regard to water supply performance, a further improvement of the post-2002 rule curves was proposed by Chiamsathit et al. (2014a), as discussed earlier in section 2.4. The new set of upper and lower rule curves was developed from the post-2002 policy using a trial-and-error procedure involving progressively shifting downward its URC and LRC (thus making available some of the buffer zone water for supply) and observing the resulting water shortage relative to the post-2002 policy. Their study used a WEAP model, resulting in the new set of upper and lower rule curves (as seen in Figure 4.7) that are below their post-2002 counterparts. Thus, the water available for allocation under the new set of rule curves would both improve overall water supply performance and, at the same time, reserve a more generous space for flood water in comparison with the post-2002 policy. The rule curves of the three policies (i.e. pre-2002, post-2002 and new set of rule curves) are summarised in Table 4.3.

Table 4.3 The ordinates of rule curves P1, P2 and P3

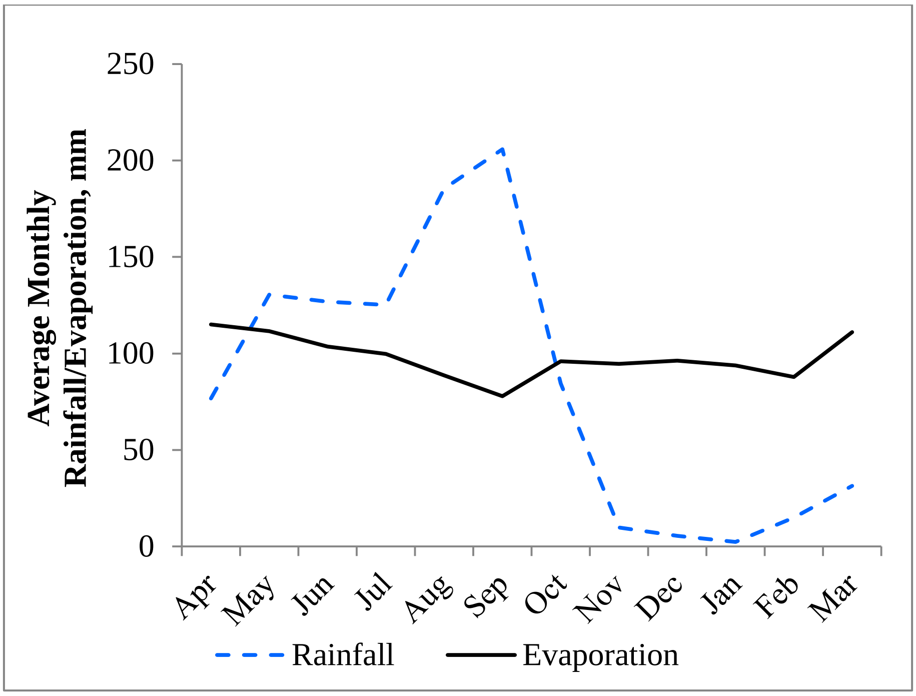
Policy	Rule Curve	Rule curve ordinates (Mm^3)											
		Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar
P1	URC	1413	1299	1151	1057	1057	1484	2071	1986	1902	1804	1678	1557
	LRC	1002	906	859	820	820	1045	1360	1315	1270	1219	1178	1082
P2	URC	1371	1176	1000	848	946	1484	2071	2071	2071	1902	1740	1557
	LRC	1002	869	797	720	772	1041	1360	1360	1360	1270	1186	1082
P3	URC	1371	1127	946	797	906	1441	1902	1902	1902	1820	1740	1557
	LRC	843	748	661	582	621	661	869	869	869	797	772	748
	FCRC	1662	1616	1571	1536	1527	1527	1902	1902	1852	1804	1756	1709


Myanmar
Loas
Cambodia
Thailand
Vietnam
N
Lam Pa nieng river
Pong river
Choen river
Phrom river
Ubonratana reservoir
Nong wai weir
Pong river
Khon Kaen
Lampao reservoir
Kalasin
Yong river
Lampao river
Chi river
Mahasarakham
Loi Et
Chaiyaphum
Yasothorn
N
0 5 10 20 30 40 50
km
Province
Streamflow guage
Basin bounadry
River
Reservoir

(a)



(b)



(c)

Figure 4.2: Study location showing: (a) Chi River basin (Chiamsathit et al., 2014); (b) derived reservoir surface area-storage relationship for Ubonratana reservoir; (c) average monthly rainfall and evaporation distribution.

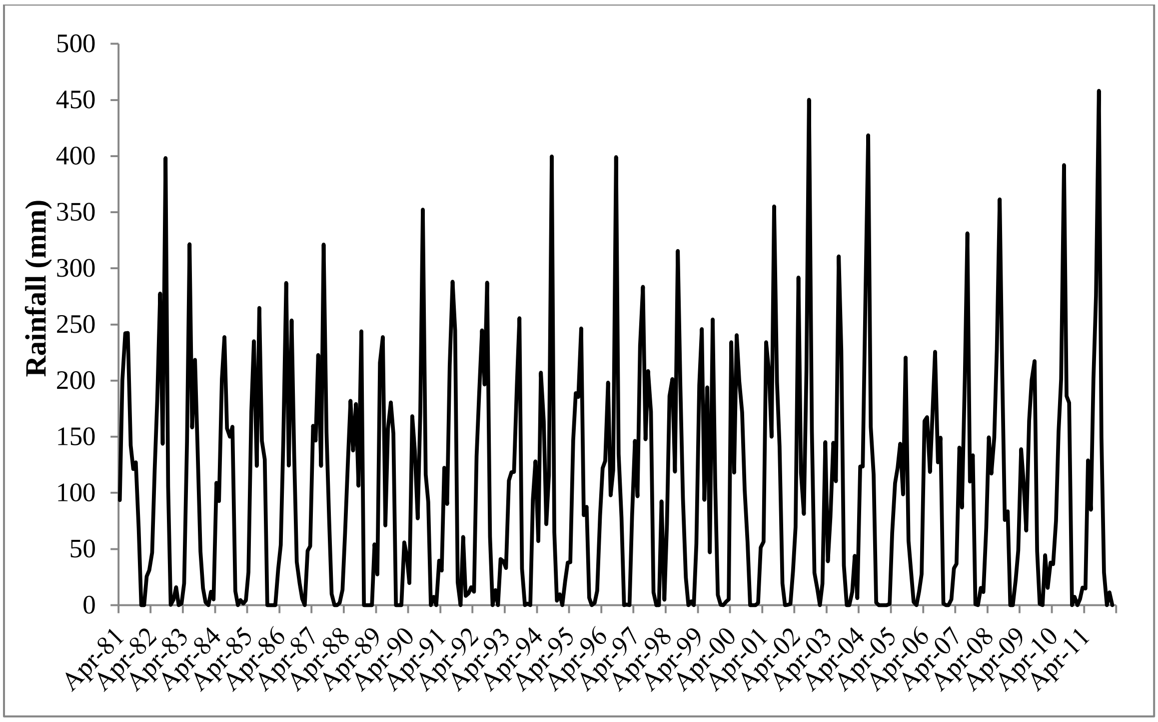


Figure 4.3 Historical monthly rainfalls at Nong wai in April 1981-March 2012

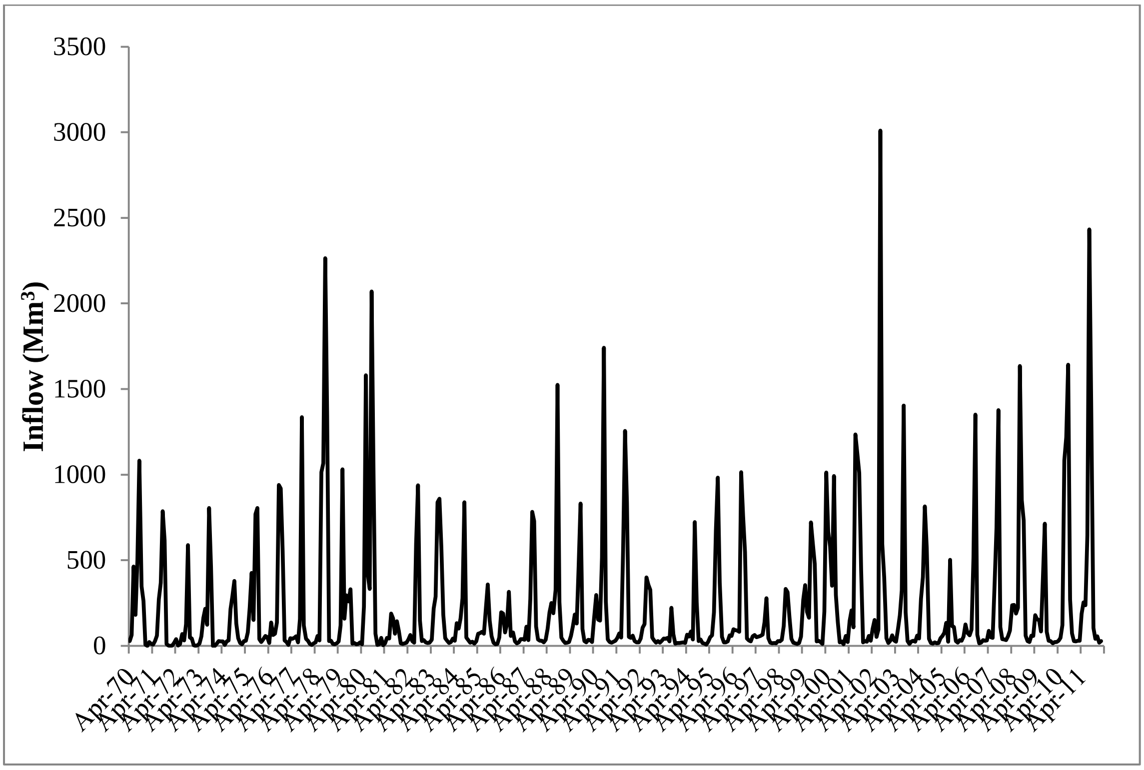


Figure 4.4 Historical inflow of the Ubonratana reservoir in April 1970-March 2012

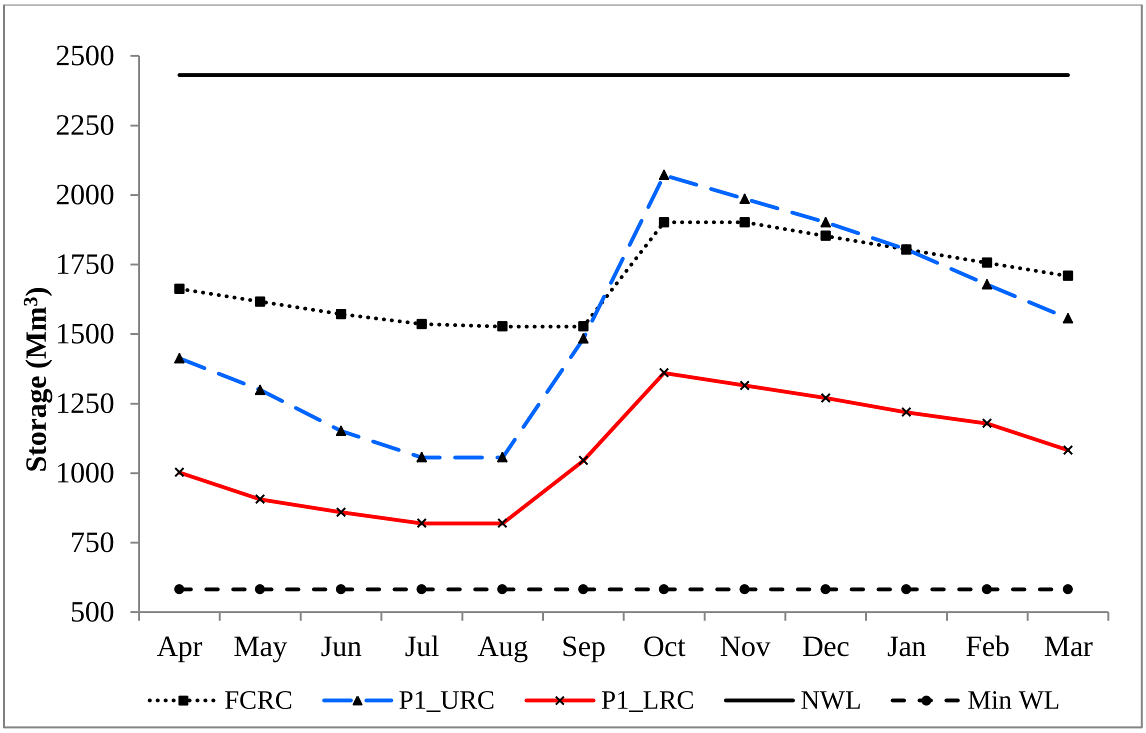


Figure 4.5 The rule curve of the policy practised pre-2002 (EGAT, 2002)

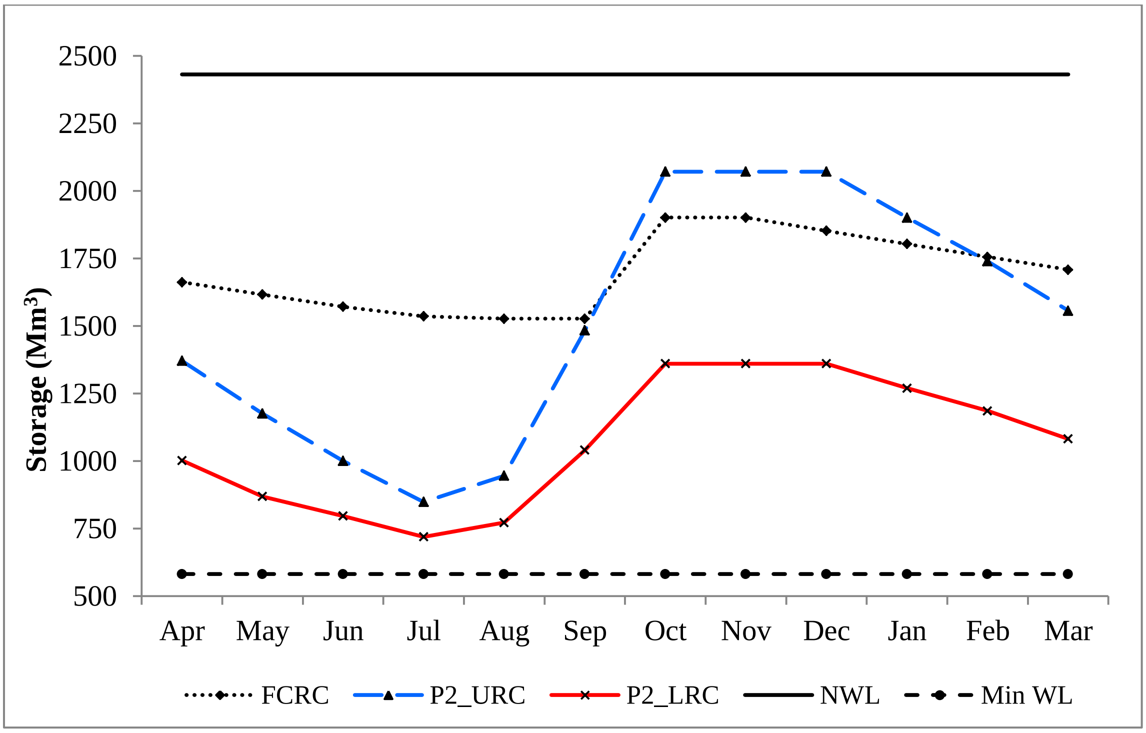


Figure 4.6 The rule curve of the policy practised post-2002 (EGAT, 2002)

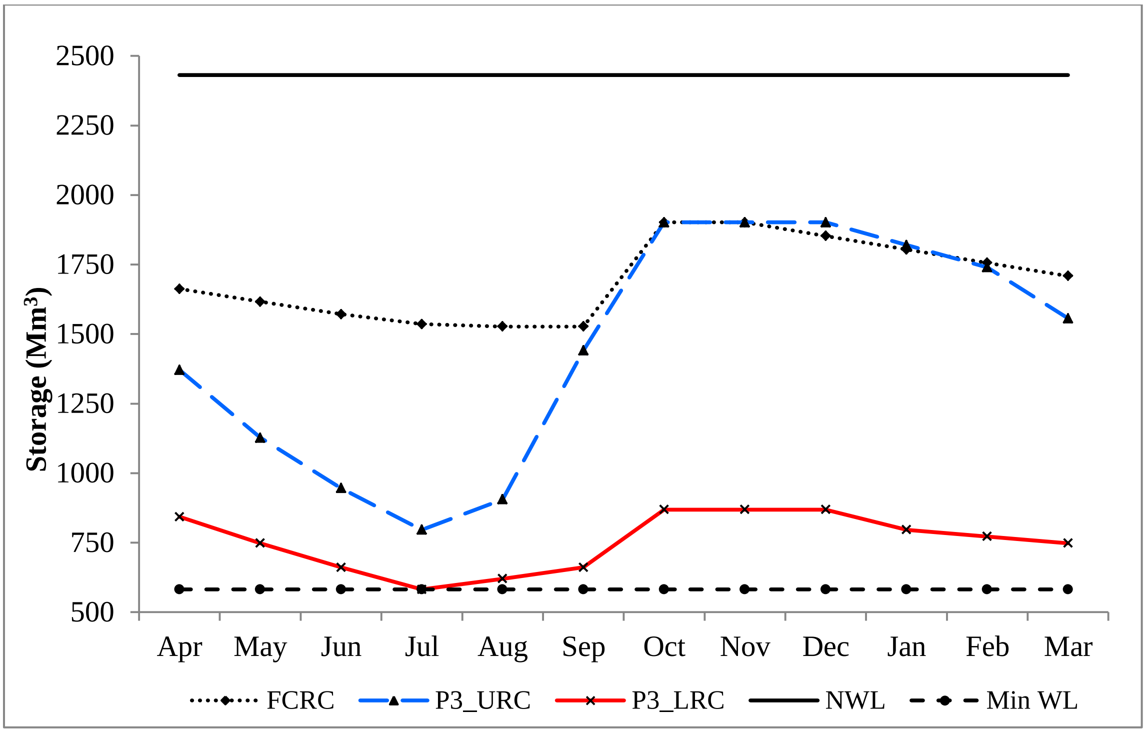


Figure 4.7 The rule curve of the newly derived policy (Chiamsathit et al., 2014a)

4.7 Summary

This chapter presents the Ubonratana reservoir in the northeastern Thailand, using it as a case study. It starts with general information about Thailand including an overview of the climatic conditions and irrigation of this region. All river basins in Thailand, including the Chi river basin where the study area is located, are presented. The characteristics and water demands of the reservoir are provided in this chapter. The data collection and its details are also included. The chapter ends with information about the Ubonratana reservoir operation including the existing rule curves. The next chapter will present the results and analysis of the data.

Chapter 5 Results and Analysis

5.1 Introduction

In this chapter, the results of the study will be presented. Given the numerous facets of the study, however, the chapter has been arranged in the following sub-sections that address specific aspects of the results.

(i) Evaluated performance of existing rule curves at Ubonratana reservoir, including the SOP.

(ii) Optimised rule curves with GA and NLP

(iii) Optimised hedging-integrated rule curves with GA

(iv) Reservoir inflow forecasts

5.2 Existing policies and their performance

5.2.1 Introduction

As reminder, two policies have been used at Ubonratana prior to the current study and a third one was proposed by Chiamsathit et al. (2014a). In order to establish the superiority of the optimised policies developed during the current study, it is necessary to assess the performance of the reservoir with these existing policies. For completeness the SOP was also evaluated. Thus, simulations were carried out using alternatively:

(i) the policy practised before 2002 (P1)

(ii) the policy practised after 2002 (P2)

(iii) the policy proposed by Chiamsathit et al. (2014a) (P3)

(iv) the SOP (P4).

Monthly data from April 1982 to March 2012 were used. The initial storage was set at 599.39×10^6 m^3 as observed on 1st April 1982 (data provided from EGAT).

5.2.2 The performance of policy practised pre-2002 (P1)

The rule curve for the operating policy, P1 had been used until 2002 to control the storage volume in the reservoir, as shown in Figure 4.5. The simulated performance in meeting the water supply target demands of this policy is summarised in Table 5.1. The water shortage for irrigation is the highest in volume because it is the lowest priority and has highest water demand. The water shortage of public demand is less than other demand because they are the first priority water users. Moreover, domestic water demands are much less compared with irrigation and downstream requirements, so their demand is satisfied most of the time periods.

The longest continuous period of shortage is 8 months, from September 1993 to April 1994. The continuous shortage periods mostly happen during the dry season (November – April). This is because the mean annual inflow volume to the reservoir in 1993 is lower than other years and especially during October to December. With the lower rule curve (LRC) also being at its highest level in this period (see Figure 4.5), it is not surprising that the volume of water released is limited.

Table 5.1 The simulation results of the failure of the policy practised pre-2002

Water user	Total water released (Mm^3)	Average water released (Mm^3/year)	Max. shortage (Mm^3/month)	Number occurrence of monthly shortages (f_d)	Number of continuous failure periods (f_s)
Domestic	350	12	0.36	10	2
Downstream	6596	220	21.84	14	6
Irrigation	20647	688	107.28	27	9
Total	27593	920			

5.2.3 The performance of the policy practised post-2002 (P2)

The simulation results for the P2 policy are shown in Table 5.2. The continuous shortage periods mostly happen during the dry season. Shortage periods of this policy and the previous policy (the pre-2002 policy) are almost the same periods. However, the volume of water shortage is higher than the pre-2002 policy. This is not surprising since in revising the target storage P1 to P2 volume was decreased compared to accommodate more flood water in the reservoir. This lowering of the URC in P2 meant that less water was available for supply leading to larger water shortages. This poor performance with respect to water supply was the impetus for the development of policy P3.

Table 5.2 The simulation results of the failure of the policy practised post-2002.

Water user	Total water released (Mm^3)	Average water released (Mm^3/year)	Max. shortage (Mm^3/month)	Number occurrence of monthly shortages (f_d)	Number of continuous failure periods (f_s)
Domestic	344	11	1.92	20	7
Downstream	6413	214	27.90	22	8
Irrigation	19919	664	116.91	44	12
Total	26676	889			

5.2.4 The performance of the policy proposed by Chiamsathit et al. (2014a), P3

P3 was developed from P2 using a trial-and-error procedure. As seen in Figure 4.7, the resulting P3 policy is in general wider than P2 (implying that more water will be supplied towards meeting the various demand), does not violate the minimum pool level for hydropower generation, and its upper rule curve (URC) is everywhere below the corresponding curve for P2, thus improving flood protection relative to P2. The simulation results for this policy are shown in Table 5.3.

As noted previously, the purpose of P3 is to improve the reservoir performance by decreasing the water shortages. As a result of lowering LRC, the conservation storage volume has been increased, which enables the water requirement to be met resulting in improve performance of the system. For example, the longest continuous period of shortage is 7 months from November 1993 to May 1994 shorter than the continuous shortage periods for P1 and P2. In addition, the volume of water shortage is less than P1 and P2, as seen in Table 5.3.

Table 5.3 The simulation results of the failure of P3

Water user	Total water released (Mm^3)	Average water released (Mm^3/year)	Max. shortage (Mm^3/month)	Number occurrence of monthly shortages (f_d)	Number of continuous failure periods (f_s)
Domestic	350	12	1.86	6	5
Downstream	6663	222	27.00	7	6
Irrigation	21169	706	68.38	18	7
Total	28182	939			

5.2.5 The performance of the standard operating policy (P4)

The standard operating policy (SOP) is the policy with the objective of minimising the shortages in water supply of the Ubonratana reservoir. Therefore, the upper rule curve is set as the maximum capacity of the reservoir (182 m (MSL) or 2,431 Mm^3) and the lower rule curve is set as its minimum water level for generating electricity (175 m (MSL) or 581.67 Mm^3). This operating policy is able to supply water as much as available water above the minimum water level store water to its full capacity. The simulation results of the SOP as seen in Table 5.4 shows there is some unmet demand or any excursion of storage below the minimum water level (see Figure 5.1).

Table 5.4 The simulation results and the performance measurement of SOP

Water user	Total water released (Mm^3)	Average water released (Mm^3/year)	Max. shortage (Mm^3/month)	Number occurrence of monthly shortages (f_d)	Number of continuous failure periods (f_s)
Domestic	353	12	0.00	0	0
Downstream	6778	226	0.00	0	0
Irrigation	21737	725	38.06	4	2
Total	28869	962			

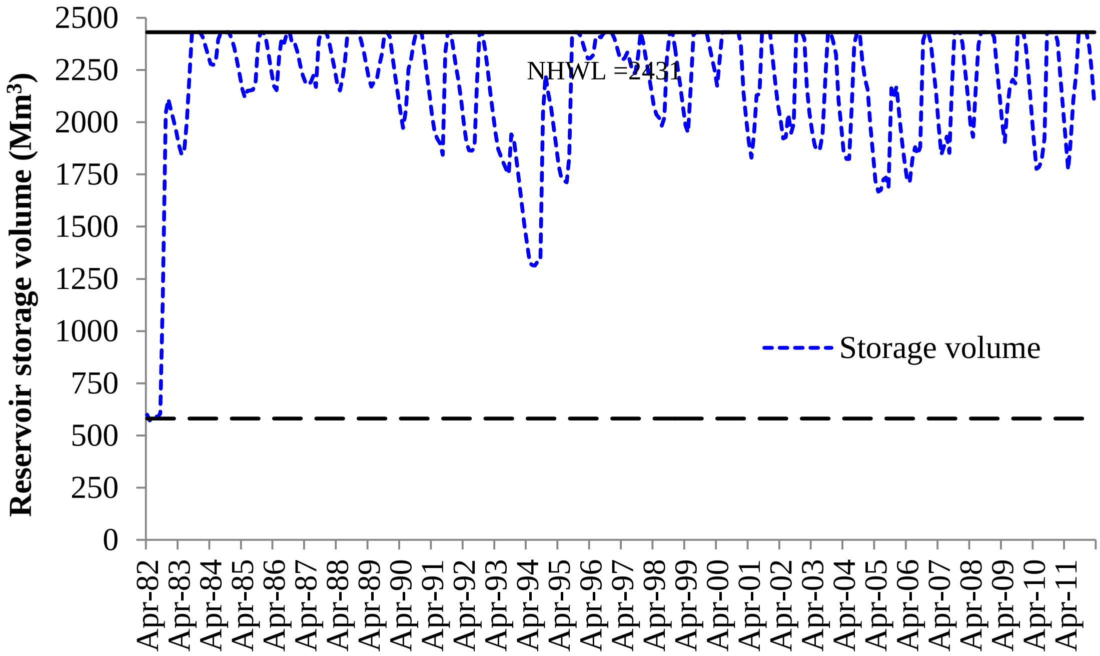


Figure 5.1 Monthly reservoir storage volume of the standard operating policy from April 1982 – March 2012

5.2.6 Performance of existing policies-further-commentary

The total unmet annual demand for each of the policies during the shortage years is shown in Figure 5.2. As can be seen, P2 recorded the highest shortfall, followed by P1 and P3 in that order. For example, while the total unmet demand for P2 was 2275.7 Mm^3, the corresponding values for P1 and P3 were 1359.4 and 769.8 Mm^3, respectively. As noted previously, P2 was meant to redress the flooding difficulties by restricting the active storage capacity; it is therefore not surprising that the conservation performance of the reservoir has significantly deteriorated as a consequence of adopting P2. The SOP has only shortfall in 1982 in Figure 5.2 which was 83 Mm^3, which is not surprising given that the SOP by default maximises the volumetric reliability (Hashimoto et al., 1982). However, the SOP could also produce high vulnerability i.e. single period shortages, if them occur, could be excessive; however, there was no such occurrence in the current study because by default all the water above the minimum hydropower pool level of 175 mamsl was available for supply with the SOP, which is not the case with P1, P2 and P3 policies.

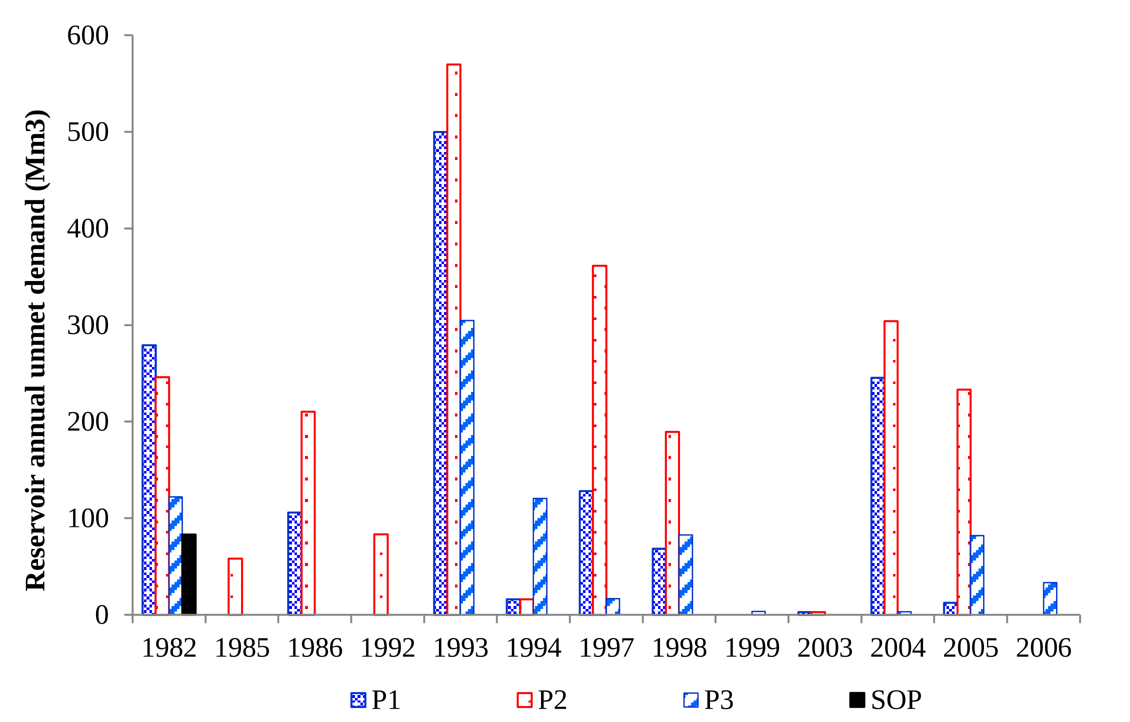


Figure 5.2 The unmet annual demand in the failure years of the simulation period (Aril1982–March2012)

The performance indices are summarised in Table 5.5. In general, the volume-based reliability R_v was always higher than the time-based reliability, as expected, which is why caution should be exercised when adopting the time-based reliability for system evaluation: the fact that time-based reliability is low does not make the water supply situation of the system poor. As noted by Adeloye (2012), while the initial evaluation of systems performance can be based on the time-based reliability R_t because it is simple to estimate and might be readily recognised by users who are already familiar with the concept of return periods, the volumetric reliability should also be evaluated and any necessary adjustments made to the system's characteristics in the light of this. For example, the R_t may be relaxed (or reduced), such as through increasing the release from the reservoir to meet additional needs or adopting a lower reservoir capacity during planning, if the R_v is very high. The volumetric reliability estimates in Table 5.5 fully support the observation made earlier regarding the relative sizes of the unmet demand by each of the policies. Additionally, the volumetric reliability tends to decrease as the sectoral priority decreases; this is also as expected. As the SOP did not produce shortages in domestic and downstream sectors, the resilience φ is undefined and the reliability measures attained their respective ultimate values as expected i.e. R_v= R_t = 1; η =0.0.

Table 5.5 Summary of evaluated reservoir performance indices for the tested policies

Policy/ water user	Water deficit (Mm^3)	Reliability (%)		φ	η	λ_{user}	λ_G
		R_t	R_v				
P1							
Domestic	2.56	97.22	99.27	0.200	1	0	
Downstream	182.95	96.11	97.30	0.429	0.775	0.453	0.444
Irrigation	1173.93	92.50	94.62	0.333	0.706	0.449	
P2							
Domestic	9.03	94.44	97.44	0.350	1	0	
Downstream	365.52	93.89	94.61	0.364	0.962	0.236	0.362
Irrigation	1901.17	87.78	91.29	0.273	0.719	0.407	
P3							
Domestic	3.25	98.33	99.08	0.833	1	0	
Downstream	115.04	98.06	98.30	0.857	0.889	0.454	0.469
Irrigation	651.53	95.00	97.01	0.389	0.697	0.482	
SOP							
Domestic	0.00	100.00	100.00	-	0	1.00*	
Downstream	0.00	100.00	100.00	-	0	1.00*	0.719
Irrigation	83.15	98.89	99.62	0.500	0.500	0.628	

* Based on two indices: R_t and η – only.

The estimated sustainability indices for each user category are shown in the penultimate column of Table 5.5, while the group sustainability is shown in the last column. For the SOP, λ in domestic and downstream sectors were computed using only R_t and η. In terms of sustainability, P2 is clearly inferior to P1 and this further confirms the water supply difficulty that had attended the introduction of P2. However, P3 is marginally better than P1 and much better than P2 in terms of the reliability and resilience. The superiority of the P3 relative to P2 is exemplified by the sustainability index for the downstream and irrigation water supply sectors, where P3 offers a system that is about 29.7% more sustainable than P2. Consequently, P3 has improved the performance of Ubonratana significantly in relation to its highest priority functions, namely, domestic and industrial water supply. However, as remarked previously, the reservoir is a multi-purpose system relied upon for flood protection in addition to its conservation needs; consequently, efforts such as P3 to improve the water supply performance should not be at the expense of the flood protection function. This is why in developing P3 it was ensured that its upper boundary was everywhere below the upper boundary for P2. Consequently, although P3 has significantly improved the water supply performance relative to P2, its flood protection function should be similar, if not better than that of P2. As expected, the sustainability index for the SOP was unity throughout.

5.2.7 Summary

This section has examined three operational strategies for the multi-purpose Ubonratana reservoir in northeastern Thailand. Using a reservoir for both flood control and conservation (water supply, downstream, irrigation) purposes creates problems for operation because, whereas the former requires the reservoir to be as empty as possible, the latter requires a reservoir that is, for most times, full so that it can meet the demands with an acceptable level of performance.

The initial set of rule curves (P1) used for the operation of the Ubonratana prior to 2002 performed the water supply function satisfactorily but failed on flooding. The post-2002 rules (P2) that replaced them reduced the flooding problem but aggravated water shortage. P3 has to remedy the post-2002 water shortage problem but should not affect the post-2002 level of protection against flooding offered by Ubonratana. This is why in developing P3 it was ensured that its upper boundary was everywhere below the upper boundary for P2. While the SOP was the best for water supply, strictly it is not a realistic option for reservoir operation when flood control is a consideration because reservoir storage can attain the maximum full capacity level with the SOP, with little or no space left in the reservoir for accommodating flood water.

The existing policies at Ubonratana have revealed deficiencies in performance especially in relation to vulnerability. This is not surprising given that they have been developed using simulation studies. The new development of the policy in the current study uses optimisation as reported in the next section.

5.3 Optimisation of reservoir operating rule curves

5.3.1 Introduction

As seen in the foregoing while the reliability (volume and time) indices were quite high and acceptable for all the tested policies, the vulnerability (or maximum single period shortages) was unacceptably high. P1, P2 and P3 were developed using simulation; optimising them will be one way of improving the vulnerability especially if the objective function is related to the water shortage.

5.3.2 Genetic algorithm optimisation for the reservoir operating rule curves

5.3.2.1 Determining GA population size and number of generations

Because the GA is initialised with random numbers which are unlikely to be the same over repeated trials or sets, the algorithm is normally repeated several times, typically 30, and either an average solution or the best among the set of 30 repetitions is represented in this study. Factors that affect the convergence include the number of generations, the population size and the number of repetitions or sets. Consequently, the SGA algorithm investigated the effect of population sizes (50, 100, 200 and 250) and generations (1-3000) on the fitness values. Then the best combination of population size and generation is applied for the SGA optimisation for this study.

Figure 5.3 shows the effect of population size on the fitness values for the SGA, from where it is clear that increasing the population above 200 does not produce any significant improvement in the fitness function. The algorithm has been run 30 times for each case to accommodate the variability associated with the random generation of the initial solution populations. The fitness plotted in Figure 5.3 represents the mean for the 30 repetitions. A population of 200 was thus adopted to test the effect of the number of generations on the fitness and the result is shown in Table 5.6. As shown in Table 5.6, while the fitness function reduced by 14.9% when the generation was increased from 100 to 1500, increasing the generation beyond 1500 produced no noticeable improvement. Thus, for the SGA implementation in the Ubonratana rule curves optimisation, it would seem that a population size of 200 and 1500 generations are the best combination.

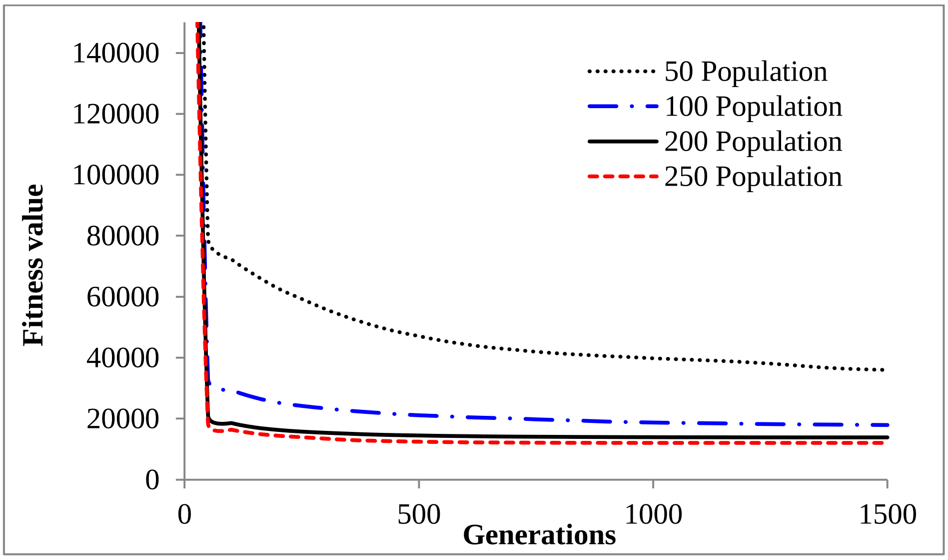


Figure 5.3 Comparison of the effect of population size

Table 5.6 Influence of number of generations on the fitness value for SGA (population = 200)

Generations	100	1500	3000
Fitness value	18569	15809	15762

5.3.2.2 Determining GA variables "g" and "r"

DGA starts with an initial random population like the SGA and runs over "g" generations and repeats "r" times. "g" and "r" are parameters of DGA and their best values were determined by trial-and-error. Consequently, the DGA algorithm was tested for generations "g" (= 2, 5, 10, 15 and 20) and repetitions "r" (= 3, 5, 7 and 10). The algorithm has been run 10 times for each case to accommodate the variability associated with the random generation of the initial solution populations, their performance (i.e. the fitness value and computational time) over 10 runs are shown in Table B1, appendix B. The average of convergence rate and the best fitness value among the set of 10 are represented in Table 5.7 and Figure 5.4, respectively. The best combination of "g" and "r" is then applied for the DGA optimisation in this study. As the results shown in the previous section, the best population size is 200, thus it was also used for the number of population size in DGA.

The effect of the number of generations (g) and repetitions (r) on the average computation time and the minimum, maximum and average fitness values are shown in Table 5.7, while Figure 5.4 depicts the variations in the best fitness function as both the 'g' and 'r' change. As expected, increasing both the 'g' and 'r' causes the computation time to increase. However, much more significant for this work is the influence of 'g' and 'r' on the fitness function. As Figure 5.4 shows, the global minimum of the fitness function was 5987 but required about 20 generations to attain with r= 5; this global minimum was also reached after only 2 generations for r=7. However, the global minimum was reached for the "r" =7 and "g" =5, but the average computation time is higher by almost 2 times taken by "r" =7 and "g" =2.

In fact, increasing the repetitions to r=10 and g =2 produced the minimum result that is indistinguishable from that of r=7, but the average convergence rate of r=10 is significantly increased by about 60% of the time taken by r=7. This implies that "g" =2 and "r"=7 represent the best combination in DGA. The best fitness value for the "r"=2 and "g"=7 combination in DGA i.e. 5987, is about 45% of the 15809 achieved with the SGA (see Table 5.6). Additionally, the average computational time for the best combination in DGA was 424 seconds (as seen in Table 5.7), i.e. less than almost 50% of time taken by the SGA. The overall computational times of running are shown in Table B2, appendix B.

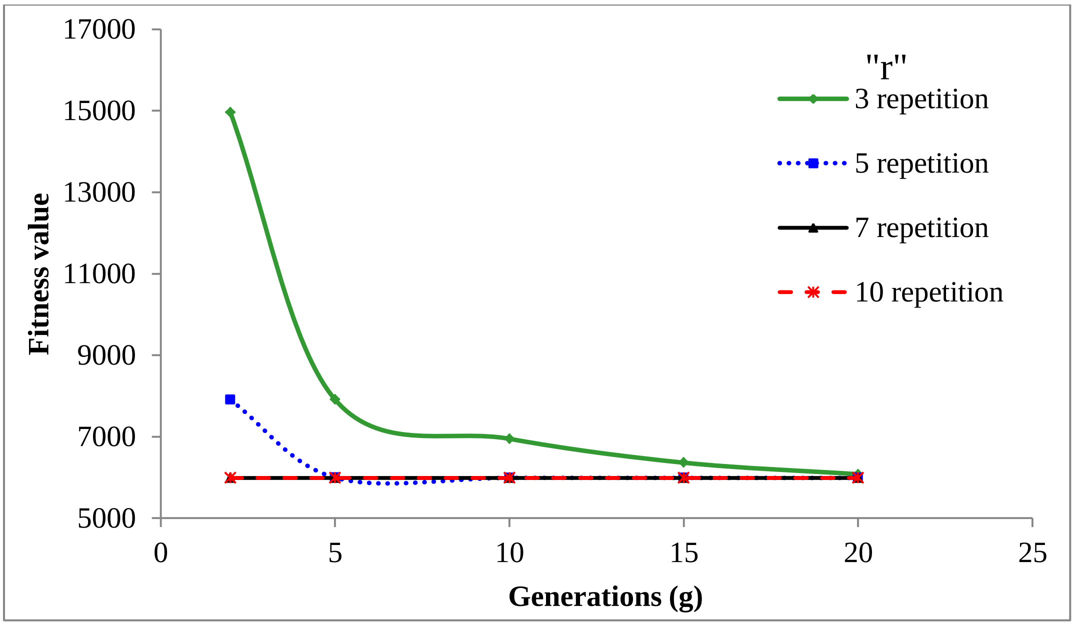


Figure 5.4 Influence of the generations and repetitive algorithm on the fitness value

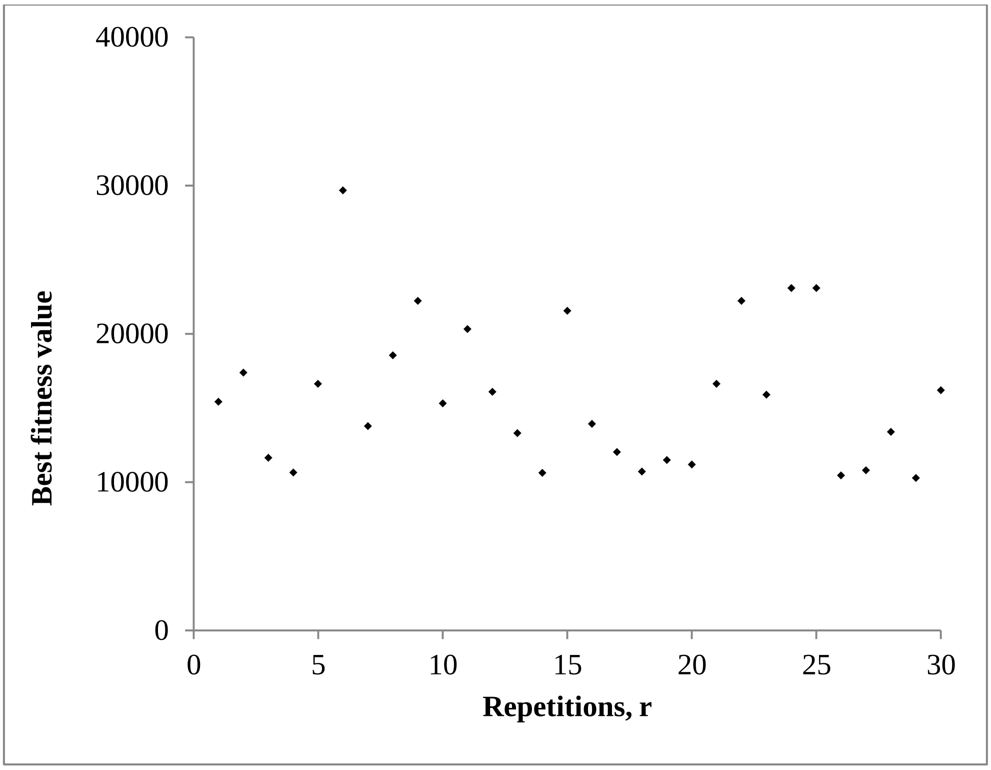
Table 5.7 The fitness values and average computation time (sec) for different “r” and “g”

Repetition, r																			
3					5					7					10				
g	fitness value			Average Convergence (sec)	g	fitness value			Average Convergence (sec)	g	fitness value			Average Convergence (sec)	g	fitness value			Average Convergence (sec)
	Min	Max	Ave			Min	Max	Ave			Min	Max	Ave			Min	Max	Ave	
2	14959	64817	30824	154	2	7903	19333	10820	347	2	5987	6983	6434	424	2	5987	13678	7688	679
5	7911	25059	13734	361	5	5995	8270	7264	487	5	5987	7296	6319	802	5	5987	7973	6436	1047
10	6949	12489	8844	501	10	5991	9300	6940	661	10	5987	7087	6290	1013	10	5987	7087	6290	1013
15	6363	9713	8346	543	15	5989	7036	6256	1162	15	5987	6037	5997	1404	15	5987	6037	5997	1404
20	6079	12111	8804	669	20	5987	6823	6356	1585	20	5987	6071	5999	1535	20	5987	6813	6080	2119

5.3.2.3 Optimised rule curves with SGA and DGA

The monthly ordinates of the URC and LRC were optimised using genetic algorithms and the sum of square of deficit used for the objective function. The complete set of the best fitness values for all 30 runs for this combination of population size and generation for SGA and DGA are shown in Figures 5.5 (a) and (b), respectively. The performance results (i.e. fitness value and computational time) over 30 runs of SGA and DGA are shown in Table B2, appendix B. This clearly demonstrates the variability in the best solution as expected, given the random nature of the initial solution population. The minimum and maximum best fitness for SGA in Figure 5.5 (a) were 10271 and 29671, while for DGA, they were 5987 and 10286, respectively. Figures 5.5 (a) and (b) show that the solutions of SGA were trapped in the local optimum unlike the solutions of DGA that were around the global optimum. Consequently, the average of the best fitness value over the 30 runs for DGA was 6709 or about 50% of SGA average of 15809. The computation time, although not plotted here, was equally variable with mean = 494 sec. for DGA and 792 sec. for SGA.

The ordinates of the optimised rule curves are listed in Table 5.8; the FCRC is the flood control rule curve which has not been optimised in this study but was based on the values provided by EGAT. Figures 5.6 (a) and (b) are the graphical illustrations of the optimised rule curves using SGA and DGA, respectively. In general, the optimised rule curves fulfil the specified constraints, since for example the rule curves are bounded by FCRC and the minimum water level for hydropower generation (Min.WL). Additionally, the optimal rule curves trajectories obtained with both SGA and DGA were well-behaved, with the nadir occurring around July/August so as to accommodate the large runoff during the monsoon, thus contributing to flood alleviation. This is to be expected given the historic inflow record used for the design of the rule curves. As the mean inflow statistics presented in Table 4.2 show the inflow runoff is highest during the Monsoon season (mid-May to mid-October) and effective reservoir operation should ensure that adequate storage is provided in the reservoir to accommodate this inflow. It is therefore not a coincidence that the nadir of the rule curves actually occurs during the Monsoon season.



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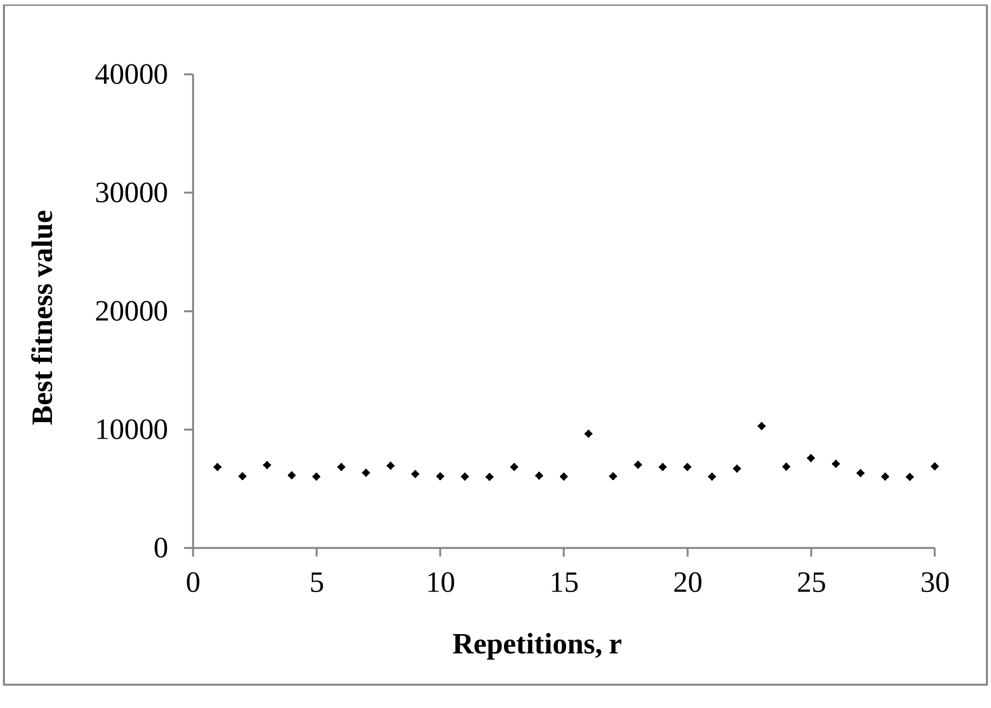


(b)

Figure 5.5 The fitness values of the algorithm of 30 repeating times for (a) SGA and (b) DGA

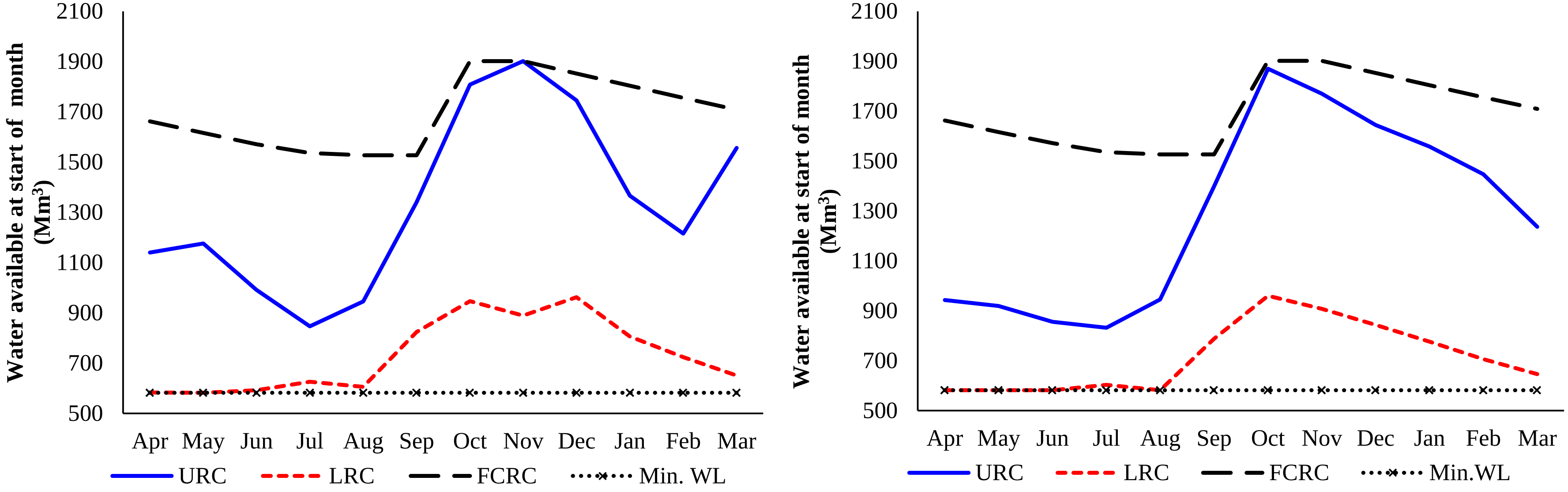
The results of simulation for SGA and DGA were compared to P3, as shown in Table 5.9. As seen in Table 5.9, in terms of the total amount of water released over the 360 months (1982-2012) of the simulation, DGA was significantly better than P3 and slightly better than SGA. In particular, the number and amount of unmet demands with DGA policy were much better than P3 and marginally better than SGA. For example, there is no water shortage at all in domestic sector for the DGA optimised policy, while only one shortage occurred in downstream sector, as seen in Table 5.9.

As seen in the Table 5.10, all performance indices of the DGA were better than those of the SGA. In terms of time-based reliability, volume-based reliability and vulnerability, the DGA was better than P3. The continuous failure sequences (f_s) and duration (f_d) were reduced in both SGA and DGA for domestic and downstream sectors, so the resilience is higher than P3. The total unmet demand in SGA and DGA was 358 and 310 Mm^3, which was almost 53% and 60% less than the policy P3, respectively. The time-based and volumetric reliability in DGA are marginally better than SGA.

The vulnerability, η of the optimised policy using DGA is significantly better than P3 in all sectors and much better than using SGA in public and downstream supply sectors. The η of irrigation sector for P3 (=0.7) is about two times as high as that for SGA and DGA (=0.36). The η of downstream sector for P3 is much higher than DGA but marginally lower than SGA. The η of domestic and downstream demand sectors in SGA was high because all failure sequences contain one full-unmet demand (as seen in Table 5.9). The optimised policy using DGA offers a system that was almost 93.3% and 31.9% more sustainable than the policy using SGA and P3, respectively.

Table 5.8 Ordinates of rule curves (Mm^3) tested by SGA and DGA

GA	Rule Curve	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar
	FCRC	1662	1616	1571	1536	1527	1527	1902	1902	1852	1804	1756	1709
SGA	URC	1141	1176	991	846	946	1340	1808	1901	1746	1366	1216	1556
	LRC	583	582	592	626	606	824	947	889	962	806	724	651
DGA	URC	943	919	856	832	946	1398	1870	1770	1644	1558	1447	1237
	LRC	582	582	582	603	582	788	960	908	843	777	707	646



(a)

(b)

Figure 5.6 The optimised rule curves at Ubonratana (a) using SGA (b) using DGA

Table 5.9 The simulation results for P3, SGA and DGA compared.

Policy	Water user	Total water released (Mm^3)	Total water shortage (Mm^3)	full unmet demand (month)	Number occurrence of monthly shortages (f_d)	Number of continuous failure periods (f_s)	Sum. of shortage per demand
P3	Domestic	350	3	6	6	5	6.0
	Downstream	6663	115	6	7	6	6.2
	Irrigation	21169	652	7	18	7	12.6
	Total	28182	770				
SGA	Domestic	352	0.53	2	2	2	2.0
	Downstream	6745	34	2	2	2	2.0
	Irrigation	21496	324	2	16	2	5.7
	Total	28594	358				
DGA	Domestic	353	0.00	0	0	0	0.0
	Downstream	6778	0.50	0	1	1	0.0
	Irrigation	21511	309	1	15	3	5.3
	Total	28642	310				

Table 5.10 Summary of evaluated reservoir performance indices for the tested policies

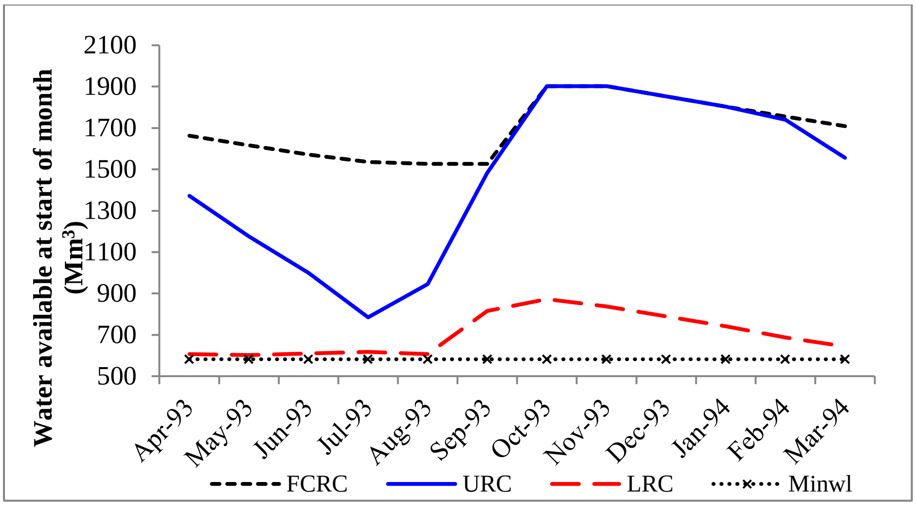
Policy	Water user	Reliability (%)		φ	η	λ_{user}	λ_G
		R_t	R_v				
P3	Domestic	98.33	99.08	0.83	1.00	0.000	0.469
	Downstream	98.06	98.30	0.86	0.889	0.454	
	Irrigation	95.00	97.01	0.39	0.697	0.482	
SGA	Domestic	99.44	99.85	1.00	1.000	0.000	0.320
	Downstream	99.44	99.50	1.00	1.000	0.000	
	Irrigation	95.56	98.51	0.13	0.358	0.425	
DGA	Domestic	100.0	100.0	-	0.000	1.000	0.619
	Downstream	99.72	99.99	1.00	0.026	0.990	
	Irrigation	95.83	98.58	0.20	0.357	0.498	

5.3.3 Testing the accuracy of the GA

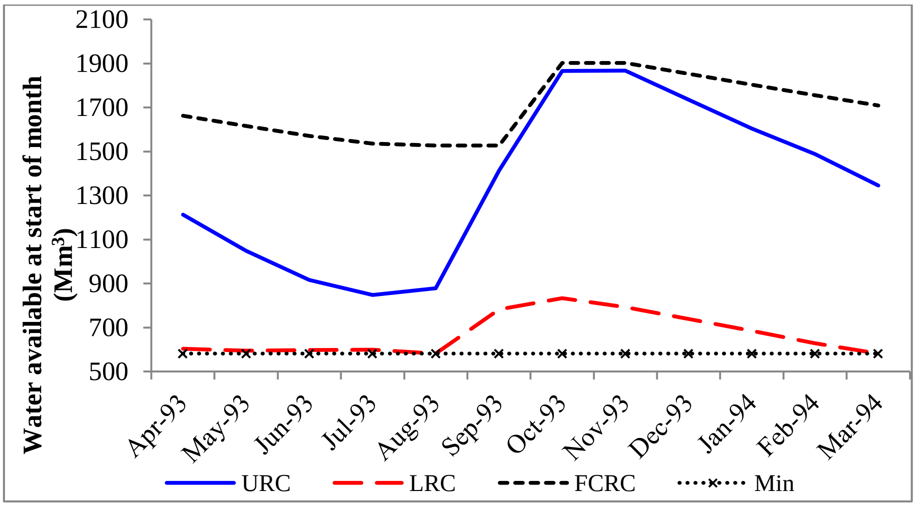
To test the accuracy of GA, a single year in the period of 1993 and 2002 are used to optimise rule curves were also derived using nonlinear programming (NLP) for the Ubonratana reservoir. The NLP implementation was carried out in LINGO (LINGO, 2004) and due to the limitation of the available version, analysis was limited to a single year. In this study, two such single years that depict the driest and most variable respectively in the record were selected. Consequently, based on evaluation of the historical data of 32-year monthly inflow of the Ubonratana reservoir shown in Table A11 (appendix A), the year with lowest mean of inflow is 1993 (April 1993-March 1994) and the year with highest CV of inflow is 2002 (April 2002-March 2003). The performance of the optimised rule curves were tested for the worst inflow situations i.e. the year with the lowest mean inflow (1993) and the year with highest inflow variability as characterised by the coefficient of variation (CV) of annual inflow (2002). The CV is the most important parameter of the streamflow process influencing reservoir capacity (Adeloye, 1990).

Figures 5.7 (a) (b) and (c) are the graphical illustrations of the optimised rule curves in 1993 using NLP, SGA and DGA, respectively, while Figures 5.8 (a), (b) and (c) are the corresponding curves in 2002. The ordinates of the optimised rule curves of 1993 and 2002 for NLP, SGA and DGA are shown in Tables 5.11. Although the plotted curves in Figures 5.7(a-c) look similar, a careful examination of the ordinates of the optimised rule curves of 1993 in Table 5.11 will show that the lower rule curve of NLP is everywhere higher than LRC of SGA and DGA, resulting in a higher total amount of shortage in NLP than both SGA and DGA. Due to the similarity of the lower rule curve of SGA and DGA, the total amounts of shortage in SGA and DGA were not significantly different. The ordinates of the optimised rule curves of 2002 show that there is no water shortage and the best fitness value is zero for SGA, DGA and NLP. This causes the search algorithm i.e. SGA and DGA to provide similar rule curves because the algorithms could find the global optimum from the initial population.

As seen in Table 5.11, the best fitness value of NLP (=22836) for the optimisation in 1993 is about 1.29 and 1.27 times as high as that for SGA (=17693) and DGA (=17675), respectively. The performance results over 30 runs in 1993 are shown in Table B3, appendix B. Additionally, the ordinates of rule curves of SGA and DGA are lower than those of NLP. This has in turn affected the volume-based reliability, R_v, in irrigation supply sectors as seen in Table 5.13 which increased from about 36.8% for NLP to about 44.4% for SGA and DGA. The results of simulation in 1993 for NLP, SGA and DGA are compared, in Table 5.12 from where it can be seen that the results of SGA and DGA were not significantly different. The number of unmet demands of the optimised policy using NLP, SGA and DGA are not different; there were 12 months shortages in irrigation sector but no shortage in domestic and downstream sectors. This caused R_t=0 for irrigation and R_t=1 for domestic and downstream sector.



(a)



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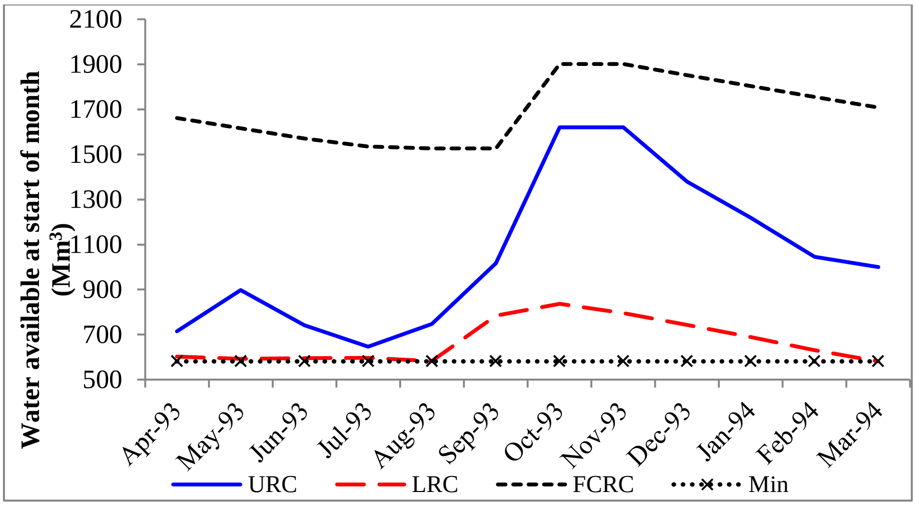
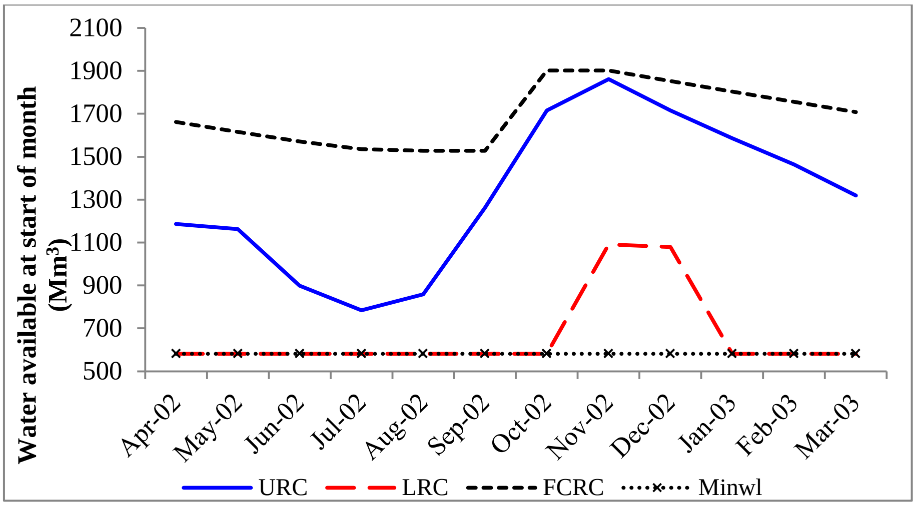
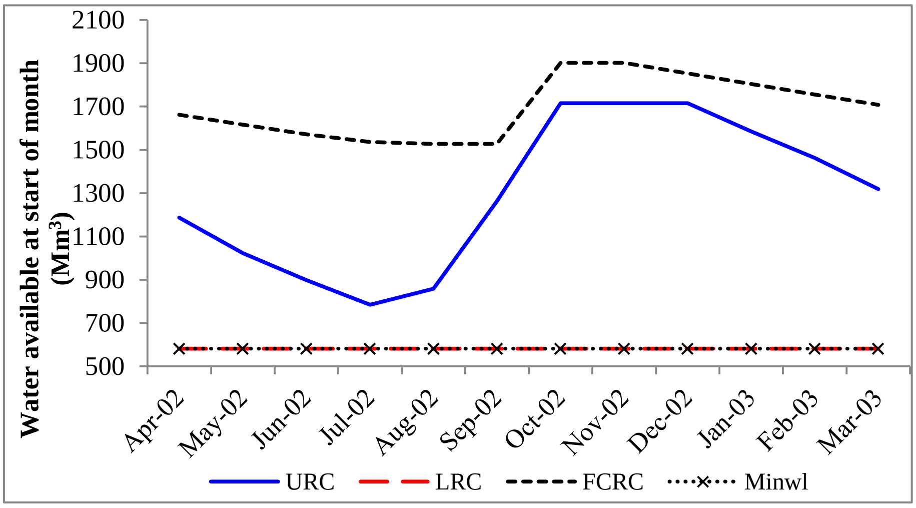


(c)

Figure 5.7 The optimised rule curves for year 1993 at Ubonratana by using (a) NLP, (b) SGA and (c) DGA



(a)



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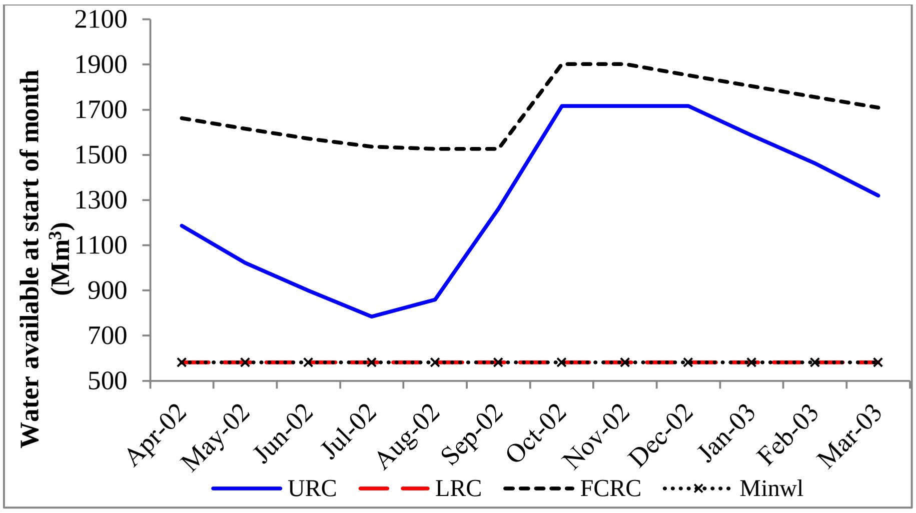


(c)

Figure 5.8 The optimised rule curves for year 2002 at Ubonratana by using (a) NLP, (b) SGA and (c) DGA

Table 5.11 The best fitness values and ordinates of rule curves (Mm^3) tested by NLP, SGA and DGA

Year	Optimisation	Fitness value	Rule Curve	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar
1993	NLP	22836	URC	1371	1176	1000	784	946	1484	1902	1902	1852	1804	1740	1557
			LRC	607	603	610	617	608	815	873	837	790	741	687	644
	SGA	17693	URC	1213	1048	917	848	879	1414	1866	1868	1735	1605	1488	1345
			LRC	603	595	597	599	583	783	834	792	739	686	629	582
	DGA	17675	URC	714	898	742	646	747	1017	1620	1620	1380	1219	1045	1000
			LRC	602	593	595	598	583	785	837	796	744	689	631	582
2002	NLP	0	URC	1187	1163	898	784	859	1262	1716	1861	1716	1586	1463	1319
			LRC	582	582	582	582	582	582	582	1091	1079	582	582	582
	SGA	0	URC	1187	1022	898	784	859	1262	1716	1716	1716	1586	1463	1319
			LRC	582	582	582	582	582	582	582	582	582	582	582	582
	DGA	0	URC	1187	1022	898	784	859	1262	1716	1716	1716	1586	1463	1319
			LRC	582	582	582	582	582	582	582	582	582	582	582	582

Table 5.12 The simulation results of the failure of tested policies in 1993.

Policy	Water user	Total water demand (Mm^3)	Total water released (Mm^3)	Total water shortage (Mm^3)	Full unmet demand (month)	Number occurrence of monthly shortages (f_d)	Number of continuous failure periods (f_s)
NLP	Domestic	3.54	3.54	0.00	0	0	0
	Downstream	200.65	200.65	0.00	0	0	0
	Irrigation	828.08	304.64	523.44	0	12	1
	Total	1032.27	508.83	523.44			
SGA	Domestic	3.54	3.54	0.00	0	0	0
	Downstream	200.65	200.65	0.00	0	0	0
	Irrigation	828.08	367.76	460.32	0	12	1
	Total	1032.27	571.95	460.32			
DGA	Domestic	3.54	3.54	0.00	0	0	0
	Downstream	200.65	200.65	0.00	0	0	0
	Irrigation	828.08	367.58	460.50	0	12	1
	Total	1032.27	571.77	460.50			

Table 5.13 Summary of evaluated reservoir performance indices for the optimised policies in 1993

Policy	Water user	Reliability (%)		φ	η	λ_{user}	λ_G
		R_t	R_v				
NLP	Domestic	100	100	-	0.00	1.00	0.198
	Downstream	100	100	-	0.00	1.00	
	Irrigation	0.00	36.79	0.08	0.63	0.00	
SGA	Domestic	100	100	-	0.00	1.00	0.198
	Downstream	100	100	-	0.00	1.00	
	Irrigation	0.00	44.41	0.08	0.56	0.00	
DGA	Domestic	100	100	-	0.00	1.00	0.198
	Downstream	100	100	-	0.00	1.00	
	Irrigation	0.00	44.39	0.08	0.56	0.00	

As seen in Table 5.11, the best fitness value of SGA and DGA for the optimisation in 2002 is zero (the fitness values of all 30 runs are zero) and equal to NLP. Additional, the ordinates of rule curves in 2002 of SGA and DGA are not different. The ordinates of rule curves of NLP are almost the same as SGA and DGA; only the ordinate values in May, November and December are higher. Because the reservoir can supply water to meet full demand, i.e. no water shortages, in all sectors for the optimised policy using NLP, SGA and DGA, as shown in Table 5.14, the time-based and volume-based reliability in all supply sectors as seen in Table 5.15 were 100% for NLP, SGA and DGA.

Table 5.14 The simulation results of the failure of tested policies in 2002.

Policy	Water user	Total water demand (Mm^3)	Total water released (Mm^3)	Total water shortage (Mm^3)	Full unmet demand (month)	Number occurrence of monthly shortages (f_d)	Number of continuous failure periods (f_s)
NLP	Domestic	22.63	22.63	0.00	0	0	0
	Downstream	351.40	351.40	0.00	0	0	0
	Irrigation	833.22	833.22	0.00	0	0	0
	Total	1207.24	1207.24	0.00			
SGA	Domestic	22.63	22.63	0.00	0	0	0
	Downstream	351.40	351.40	0.00	0	0	0
	Irrigation	833.22	833.22	0.00	0	0	0
	Total	1207.24	1207.24	0.00			
DGA	Domestic	22.63	22.63	0.00	0	0	0
	Downstream	351.40	351.40	0.00	0	0	0
	Irrigation	833.22	833.22	0.00	0	0	0
	Total	1207.24	1207.24	0.00			

The inflow recorded in 1993 was lowest mean inflow caused the severe drought, so the minimisation related to water shortages was more complex than that in 2002 which has higher amount of inflow even though it also exhibited the highest variability. As discussed earlier, the optimisation of the reservoir rule curves in 1993 shows that GA is superior to NLP. The NLP optimisation has performance as high as GA in the 2002 simulation, where there was enough water to meet full demand. The implication of the outcome of this test, together with that of the Shaffer's F7 test reported in Chapter 3 is that the DGA development reported in this study is correct and that high confidence can be had in its outcome.

Table 5.15 Summary of evaluated reservoir performance indices for the optimised policies in 2002

Policy	Water user	Reliability		φ	η	λ_{user}	λ_G
		R_t	R_v				
NLP	Domestic	100	100	-	0	1	1
	Downstream	100	100	-	0	1	
	Irrigation	100	100	-	0	1	
SGA	Domestic	100	100	-	0	1	1
	Downstream	100	100	-	0	1	
	Irrigation	100	100	-	0	1	
GA	Domestic	100	100	-	0	1	1
	Downstream	100	100	-	0	1	
	Irrigation	100	100	-	0	1	

5.3.4 Summary

This study has developed the optimised rule curves of the Ubonratana reservoir using the standard Genetic algorithm (SGA) and a new approach of dynamic GA (DGA). The sum of square of deficit was used for the objective function. The study investigated the effect of population sizes (50, 100, 200 and 250) and generations (1-3000) on the fitness values of SGA. The results showed that for the SGA implementation in the Ubonratana rule curves optimisation, it would seem that a population size of 200 and 1500 generations are the best combination. The DGA algorithm was tested for generations "g" (= 2, 5, 10, 15 and 20) and repetitions "r" (= 3, 5, 7 and 10). The results showed that "g"=2 and "r"=7 represent the best combination in DGA. Therefore, the combination of population size and generations in SGA and combination of "g" and "r" in DGA were recommended for the optimisation in this study.

A comparison of the performance of the reservoir when operated with the rule curves optimised with SGA and DGA showed that the DGA curves were far superior to the SGA and P3 curves. The group sustainability, λ_G for DGA (=0.62) is almost two times as high as that for SGA (=0.32) and it was about 1.3 times as high as that for P3 (=0.47). A further attribute of the DGA is its speed at arriving at the global optimum. For example, recorded computational times for the DGA were on average about half of those required by a standard algorithm solving the same problem. However, the optimised rule curves using SGA and DGA reduced the total water shortage in P3 over the period of April 1982- March 2012 (360 months) from 770 Mm^3 to 358 Mm^3 for SGA and 310 Mm^3 for DGA. The vulnerability, η in all sectors for DGA are significant better than that for P3, but only η in irrigation sector for SGA is better than that for P3.

The GA (i.e. SGA and DGA) was tested the accuracy of the optimised rule curves by comparing the performance to NLP. The lowest mean in 1993 and highest CV of inflow in 2002 were selected to represent the most challenge low inflow and variability of inflow, respectively. The best fitness value in the optimisation of rule curves in 1993 for NLP (=22836) was about 29% and 27% higher than that for SGA (=17693) and DGA (=17675). The best fitness value in the optimisation of rule curves in 2002 for NLP and GA were equal to zero which there was no deficit. The results show that the performance of GA optimisation is better than NLP especially in the complex problem, while NLP optimisation has performance as high as GA in the simple problem.

5.4 Optimisation of hedging rules for development of reservoir operating policy

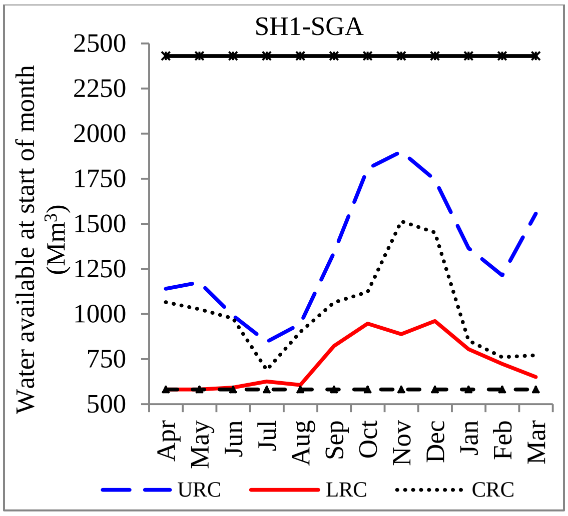
5.4.1 Introduction

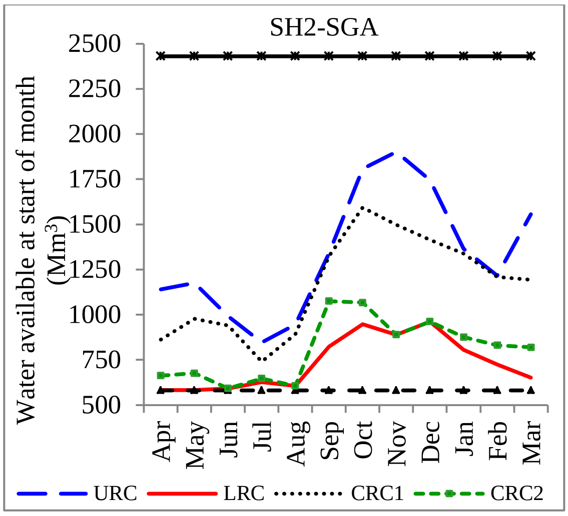
Although the optimised rule curves reduced the system vulnerability when compared to the existing policy, P3, the resulting vulnerability indices reported in Table 5.10 were still unacceptably high. For example, the SGA vulnerability for some of the users was 100% whereas in general vulnerability over 25% is not recommended because it can cause severe stress for users (Fiering, 1967). Thus, integrating hedging with the optimisation formulation for the hedging was presented in section 3.4 and the results are summarised in the following subsection.

5.4.2 Optimisation of hedging policy related to the SS objective function

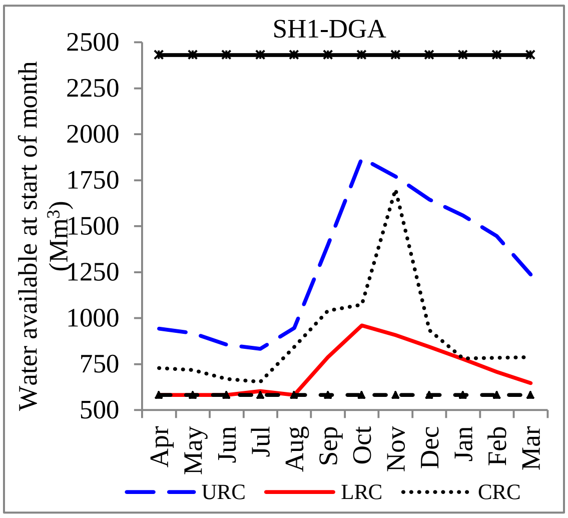
For convenience, the optimal single-stage hedging rule using the sum squares of the period shortages (SS) for the objective function for SGA and DGA are denoted by SH1-SGA and SH1-DGA, respectively, while the optimal two-stage hedging using SGA and DGA are denoted by SH2-SGA and SH2-DGA, respectively. The algorithms were run 30 times for each case, and the best performance value was selected, the fitness values over 30 runs are shown in Table B4, appendix B. The minimum best fitness values over 30 runs of SH1-SGA and SH2-SGA were 14813 and 14113, respectively, while the minimum best fitness values of SH1-DGA and SH2-DGA were 8046 and 7363, respectively. The best fitness values for SH1-SGA and SH2-SGA is about 1.8 and 2 times as high as that for SH1-DGA and SH2-DGA, respectively. The best fitness values of the two-stage hedging were reduced from the single-stage hedging about 4.7% for SGA and 8.5% for DGA. This implies that the single shortages in the two-stage hedging are smaller than the single-stage hedging.

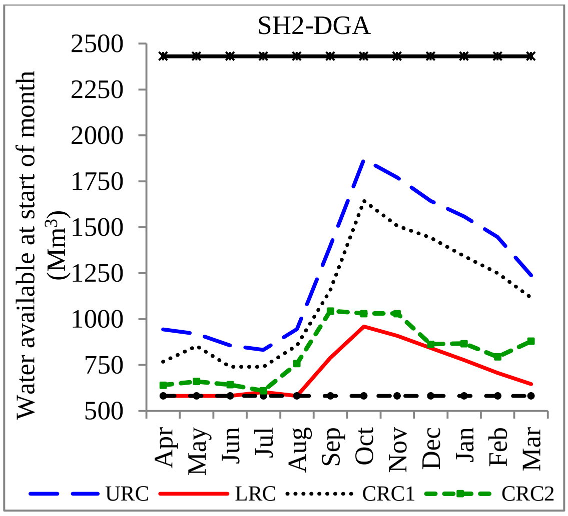
The decision variables of the optimal hedging for SH1-SGA, SH2-SGA, SH1-DGA and SH2-DGA are shown in Table 5.16. The CRC is the critical rule curve that triggers hedging and "α" is the rationing factor. Figures 5.9 (a), (b), (c) and (d) are the graphical illustrations of the optimal hedging policies for SH1-SGA, SH2-SGA, SH1-DGA and SH2-DGA, respectively. In general, the optimised critical rule curves fulfil the specified constraints since, for example, both critical rule curves are bounded by the upper and lower rule curves, and the second stage critical rule curve is everywhere below the first stage critical curve for the two-stage hedging policy. As seen in Figures 5.9 (a), (b), (c) and (d), normal operation in which the supply of full demand is attempted only occurs when the reservoir storage is outside the critical storage zones.





(a) (b)





(c) (d)

Figure 5.9 Optimal hedging rules at Ubonratana for (a) SH1-SGA, (b) SH2-SGA, (c) SH1-DGA and (d) SH2-DGA

Table 5.16 Ordinates (Mm^3) of derived hedging-integrated policies

Policy	α	Rule Curve	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar
SGA	-	URC	1141	1176	991	846	946	1340	1808	1901	1746	1366	1216	1556
		LRC	583	582	592	626	606	824	947	889	962	806	724	651
SH1-SGA	0.945	CRC	1065	1027	976	690	901	1065	1123	1515	1452	853	762	772
SH2-SGA	0.977	CRC1	862	976	940	740	893	1324	1593	1497	1415	1338	1209	1193
	0.827	CRC2	663	676	592	647	606	1075	1067	889	962	876	831	819
DGA	-	URC	943	919	856	832	946	1398	1870	1770	1644	1558	1447	1237
		LRC	582	582	582	603	582	788	960	908	843	777	707	646
SH1-DGA	0.899	CRC	729	718	669	653	844	1039	1074	1700	935	781	784	788
SH2-DGA	0.979	CRC1	767	854	740	740	857	1157	1644	1508	1444	1342	1250	1115
	0.713	CRC2	640	660	643	610	758	1044	1030	1030	863	866	794	879

The optimised rationing ratios obtained, also shown in Table 5.16, are well behaved, with both SH2-SGA and SH2-DGA "α" values being lower than their corresponding first stage values. Thus, while only 94.5% and 89.9% of the full demand were met for both SH1-SGA and SH1-DGA, respectively, for the single-stage hedging, the first stage of the rationing in the two-stage hedging met much higher, i.e. 97.7% and 97.9% for SH2-SGA and SH2-DGA respectively. For the two-stage hedging, the second stage rationing is more restricted (i.e. less water is supplied) than the rationing of the first stage, and also less than the single-stage rationing, as expected.

Table 5.17 The simulation results of the failure of derived hedging-integrated policies.

Policy	Water user	Total water released (Mm^3)	Total water shortage (Mm^3)	full unmet demand (month)	Number occurrence of monthly shortages (f_d)	Number of continuous failure periods (fs)
SGA	Domestic	352	0.53	2	2	2
	Downstream	6745	34	2	2	2
	Irrigation	21496	324	2	16	2
	Total	28594	358			
DGA	Domestic	353	0	0	0	0
	Downstream	6778	0.5	0	1	1
	Irrigation	21511	309	1	15	3
	Total	28642	310			
SH1-SGA	Domestic	352.5	0.5	2	2	2
	Downstream	6737.1	41.4	2	7	6
	Irrigation	21410.6	410	2	49	20
	Total	28500.1	451.9			
SH1-DGA	Domestic	353	0	0	0	0
	Downstream	6772.3	6.2	0	2	2
	Irrigation	21447.9	372.6	0	26	11
	Total	28573.3	378.8			
SH2-SGA	Domestic	352.5	0.5	2	2	2
	Downstream	6742.7	36.1	2	6	6
	Irrigation	21368.5	452	2	81	21
	Total	28463.4	488.7			
SH2-DGA	Domestic	353	0	0	0	0
	Downstream	6777.2	1.2	0	2	2
	Irrigation	21367.5	453.1	0	63	17
	Total	28497.7	454.3			

As seen in Table 5.17, in term of the total amount of water released over the 360 months of the simulation, the single-stage hedging (i.e. SH1-SGA and SH1-DGA) was better than the two-stage hedging (i.e. SH2-SGA and SH2-DGA); however, this may have masked incidences of larger single period shortages with the single-stage as measured by the vulnerability (η). The vulnerability of irrigation for SH1-SGA and SH1-DGA is about 1.7 and 2 times as high as that for SH2-SGA and SH2-DGA.

Table 5.17 also reveals that the hedging policies using DGA is superior to SGA in terms of the amount of water deficit, the total water shortages of SH1-SGA (=451.9Mm^3) and SH2-SGA (=488.6Mm^3) were 16% and 7% higher than SH1-DGA (=378.8Mm^3) and SH2-DGA (=454.3Mm^3), respectively. SH1-SGA and SH2-SGA recorded two months with full unmet demand but there was no record of full unmet demand for SH1-DGA and SH2-DGA. Additionally, the superiority of the SH1- and SH2-DGA relative to SH1-and SH2-SGA, respectively, is exemplified by the group sustainability index, where SH1-and SH2-DGA offered a system that was almost 7.4% and 8.2% more sustainable than SH1-and SH2-SGA, respectively.

On reliability in Table 5.17, while the number of occasions of shortages in the irrigation sector was 49 and 26 for SH1-SGA and SH1-DGA, respectively, these have grown to 81 and 63 for SH2-SGA and SH2-DGA, respectively. This has in turn affected the time-based reliability, R_t, of the irrigation sector as seen in Table 5.18 which deteriorated from about 87.2% and 93.2% for SH1-SGA and SH1-DGA to 78.9% and 83.6% for SH2-SGA and SH2-DGA, respectively. However, increasing the number of occasions of shortages for the two-stage hedging has not significantly affected the volume based reliability, R_v as expected.

The results of the tested hedging policies were compared to the optimal rule curves without hedging (i.e. SGA and DGA) shown in Tables 5.9 and 5.10. As seen in Table 5.9, in terms of total amount of water released, the without hedging amounts were SGA (=358 Mm^3) and DGA (=310 Mm^3), much lower than the corresponding results for the hedging policies. The number of full-unmet demand in irrigation without hedging (DGA) was reduced from one to zero with the hedging policies. This impinged on the vulnerability in the irrigation sector where without the hedging value for SGA (=0.358) was reduced 2.1 times for SH1-SGA and 3.6 times for SH2-SGA. For DGA (=0.357), the reduction was 1.4 times for SH1-DGA and 2.8 times SH2-DGA. Additionally, the hedging policies were better than without hedging in terms of the group sustainability index, where SH1-and SH2-SGA offered a system that were about 2.1 and 2 times, respectively, more sustainable than SGA, while SH1-and SH2-DGA were about 1.2 and 1.1 times, respectively, more sustainable than DGA. SH1-DGA was better than SH2-DGA in terms of all the performance metrics except the volume-based reliability R_v. This may be explained by the prioritisation scheme for allocating the water at Ubonratana where as noted before, the winner takes all. Thus, in the second zone of the hedging where the water available is much less, the low priority uses, e.g. irrigation, will fail more, thus leading to an overall deterioration in performance. A situation where water is allocated according to a set of weights is likely to produce a different outcome for SH2-DGA but this was not investigated in the study.

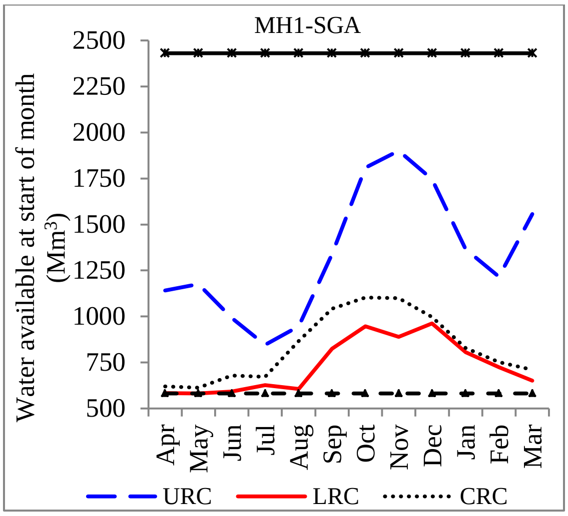
Table 5.18 Summary of evaluated reservoir performance indices for derived hedging-integrated policies

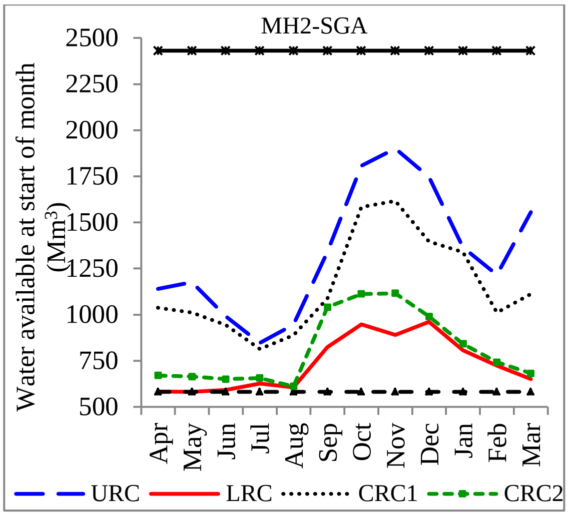
Policy	Water user	Reliability (%)		φ	η	λ_{user}	λ_G
		R_t	R_v				
SGA	Domestic	99.44	99.85	1	1	0	0.32
	Downstream	99.44	99.5	1	1	0	
	Irrigation	95.56	98.51	0.13	0.358	0.425	
DGA	Domestic	100	100	-	0	1	0.619
	Downstream	99.72	99.99	1	0.026	0.99	
	Irrigation	95.83	98.58	0.2	0.357	0.498	
SH1-SGA	Domestic	99.48	99.85	1	1	0	0.695
	Downstream	98.18	99.39	0.857	0.328	0.827	
	Irrigation	87.24	98.12	0.408	0.172	0.665	
SH1-DGA	Domestic	100	100	-	0	1	0.746
	Downstream	99.48	99.91	1	0	0.998	
	Irrigation	93.23	98.29	0.423	0.258	0.664	
SH2-SGA	Domestic	99.48	99.85	1	1	0	0.631
	Downstream	98.44	99.47	1	0.35	0.862	
	Irrigation	78.91	97.93	0.259	0.099	0.569	
SH2-DGA	Domestic	100	100	-	0	1	0.683
	Downstream	99.48	99.98	1	0.022	0.991	
	Irrigation	83.59	97.92	0.27	0.127	0.582	

5.4.3 Optimisation of hedging policy related to the MSI objective function

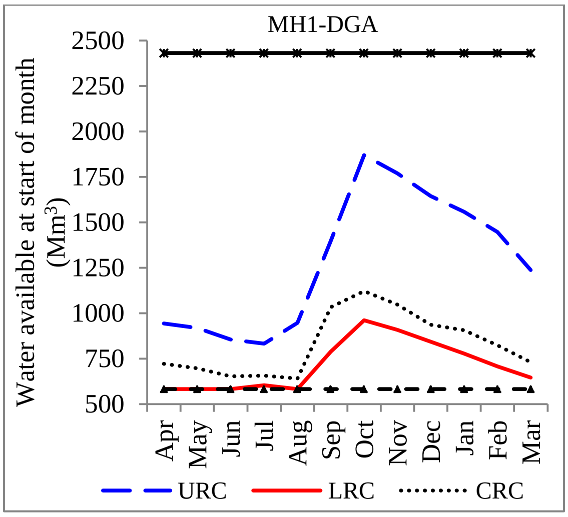
For convenience, the optimal single-stage hedging rule using the modified index shortages (MSI) for the objective function for SGA and DGA are denoted by MH1-SGA and MH1-DGA, respectively, while the optimal two-stage hedging using SGA and DGA are denoted by MH2-SGA and MH2-DGA, respectively. The algorithms were run 30 times for each case, and the best performance value was selected, the fitness values over 30 runs are shown in Table B4, appendix B. The minimum best fitness values over 30 runs of MH1-SGA and MH2-SGA were 1.20 and 0.96, respectively, while the minimum best fitness values of MH1-DGA and MH2-DGA were 0.57 and 0.54, respectively. The best fitness values for MH1-SGA and MH2-SGA is about 2.1 and 1.8 times as high as that for MH1-DGA and MH2-DGA, respectively. The best fitness values of the two-stage hedging were reduced from the single-stage hedging about 20% for SGA and 5% for DGA. This implies that the single shortages in the two-stage hedging of the MSI objective function are also smaller than the single-stage hedging.

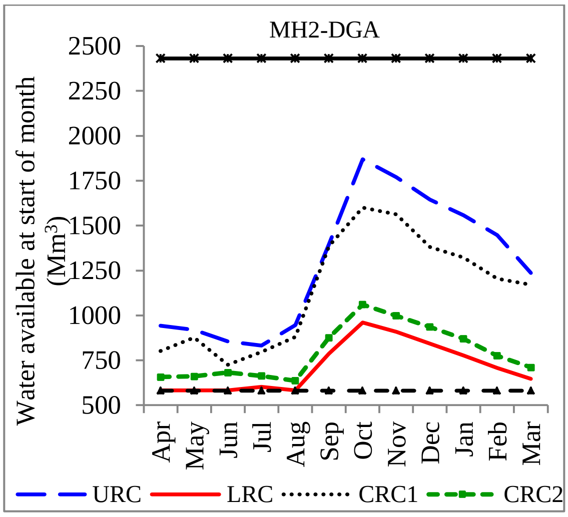
The decision variables of the optimal hedging for MH1-SGA, MH2-SGA, MH1-DGA and MH2-DGA are shown in Table 5.19. Figures 5.10 (a), (b), (c) and (d) are the graphical illustrations of the optimal hedging policies for MH1-SGA, MH2-SGA, MH1-DGA and MH2-DGA, respectively. The optimised rationing ratios obtained also shown in Table 5.19 are well behaved, with all hedging policies α_p value being higher than other users' rationing factor because of its priority.





(a) (b)





(c) (d)

Figure 5.10 Optimal hedging rules at Ubonratana for (a) MH1-SGA, (b) MH2-SGA, (c) MH1-DGA and (d) MH2-DGA

Table 5.19 Ordinates (Mm^3) of derived hedging-integrated policies

Policy	The rationing factors Public (α_p)	In-stream (α_d)	Irrigation (α_i)	Rule Curve	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar
SGA		-		URC	1141	1176	991	846	946	1340	1808	1901	1746	1366	1216	1556
				LRC	583	582	592	626	606	824	947	889	962	806	724	651
MH1-SGA	0.995	0.891	0.510	CRC	619	612	679	671	867	1043	1102	1099	997	828	751	710
MH2-SGA	0.989	0.982	0.944	CRC1	1037	1011	943	814	889	1089	1583	1616	1396	1338	1012	1111
	0.985	0.902	0.528	CRC2	670	665	651	657	612	1041	1112	1116	990	842	742	681
DGA		-		URC	943	919	856	832	946	1398	1870	1770	1644	1558	1447	1237
				LRC	582	582	582	603	582	788	960	908	843	777	707	646
MH1-DGA	0.998	0.895	0.703	CRC	721	697	652	656	641	1032	1122	1046	937	906	824	731
MH2-DGA	0.999	0.996	0.980	CRC1	802	877	726	796	880	1386	1599	1562	1382	1322	1205	1170
	0.998	0.889	0.683	CRC2	657	661	682	663	636	876	1061	998	936	870	776	710

As seen in Table 5.20, in terms of the amount of water released over the 360 months of the simulation, single-stage hedging (MH1-SGA and MH1-DGA) was better than two-stage hedging (MH2-SGA and MH2-DGA) as expected. This is, therefore not surprising that the vulnerability of domestic, downstream and irrigation for the MH1-DGA was about 1.7, 4.7 and 4.4 times as high as that for the MH2-DGA (as seen in Table 5.21). The vulnerability of downstream and irrigation for the MH1-SGA was about 4.1 and 3.9 times as high as that for the MH2-SGA. Table 5.20 also reveals that the hedging policies using DGA is superior to SGA in term of the amount of water deficit, the total water shortage of MH1-SGA (=481 Mm^3) and MH2-SGA (=577 Mm^3) were about 32% and 41% higher than MH1-DGA (=363 Mm^3) and MH2-DGA (=396 Mm^3), respectively.

On reliability in Table 5.20, while the number of occasions of shortages in the irrigation sector was 16 and 17 for MH1-SGA and MH1-DGA, respectively, these have grown to 76 and 83 for MH2-SGA and MH2-DGA, respectively. This has in turn affected the time-based reliability, R_t, of the irrigation sector as seen in Table 5.21 which deteriorated from 95.6% for both MH1-SGA and MH1-DGA to 78.9% and 76.9% for MH2-SGA and MH2-DGA, respectively. However, increasing the number of occasions of shortages for the two-stage hedging has not significantly affected the volume-based reliability R_v as expected.

The results of the derived hedging policies using the MSI objective function were compared to the derived hedging policies using the SS objective function shown in Table 5.18. In terms of total water shortages, the SS objective function using the SGA optimisation were SH1-SGA (=452 Mm^3) and SH2-SGA (=489 Mm^3) lower than the corresponding results for the MSI objective function; however, using the DGA optimisation were SH1-DGA (=379 Mm^3) and SH2-DGA (=454 Mm^3) higher than the corresponding results for the MSI objective function. In terms of the group sustainability index, λ_G the hedging policies using the SS objective function were better than those using the MSI objective function as seen in Tables 5.18 and 5.21, where SH1-SGA (=0.695), SH1-DGA (=0.746), SH2-SGA (=0.631), and SH2-DGA (=0.683) offered a system that were about 17.8%, 39.7%, 16.4% and 28.4% more sustainable than MH1-SGA, MH1-DGA, MH2-SGA, and MH2-DGA, respectively. However, the hedging policies using the MSI objective function are better than those using the SS objective function in terms of the vulnerability, η, in the high priority demand (i.e. domestic sector), for example, it was reduced from 1 (SH1-SGA) to 0.005 (MH1-SGA) for the single-stage hedging and it was reduced from 1 (SH2-SGA) to 0.011 (MH2-SGA) for the two-stage hedging. Additionally, there was no record of full-unmet demand for any hedging policies using the MSI objective function.

Table 5.20 The simulation results of the failure of derived hedging-integrated policies

Policy	Water user	Total water released (Mm^3)	Total water shortage (Mm^3)	full unmet demand (month)	Number occurrence of monthly shortages (f_d)	Number of continuous failure periods (*fs*)
SGA	Domestic	352	0.53	2	2	2
	Downstream	6745	34	2	2	2
	Irrigation	21496	324	2	16	2
	Total	28594	358			
DGA	Domestic	353	0	0	0	0
	Downstream	6778	0.5	0	1	1
	Irrigation	21511	309	1	15	3
	Total	28642	310			
MH1-SGA	Domestic	353	0.03	0	12	6
	Downstream	6757.3	21.1	0	12	6
	Irrigation	21361	459.5	0	16	5
	Total	28471.3	480.7			
MH1-DGA	Domestic	353	0.01	0	16	3
	Downstream	6751.5	27	0	16	3
	Irrigation	21484.3	336.2	0	17	4
	Total	28588.9	363.2			
MH2-SGA	Domestic	352.3	0.7	0	75	17
	Downstream	6742.6	35.9	0	75	17
	Irrigation	21279.8	540.7	0	76	17
	Total	28374.7	577.3			
MH2-DGA	Domestic	352.9	0.07	0	81	19
	Downstream	6747.6	30.9	0	82	18
	Irrigation	21455.9	364.7	0	83	17
	Total	28556.3	395.7			

Table 5.21 Summary of evaluated reservoir performance indices for derived hedging-integrated policies

Policy	Water user	Reliability (%)		φ	η	λ_{user}	λ_G
		R_t	R_v				
SGA	Domestic	99.44	99.85	1	1	0	0.32
	Downstream	99.44	99.5	1	1	0	
	Irrigation	95.56	98.51	0.13	0.358	0.425	
DGA	Domestic	100	100	-	0	1	0.619
	Downstream	99.72	99.99	1	0.026	0.99	
	Irrigation	95.83	98.58	0.2	0.357	0.498	
MH1-SGA	Domestic	96.67	99.99	0.5	0.005	0.783	0.59
	Downstream	96.67	99.69	0.5	0.109	0.755	
	Irrigation	95.56	97.89	0.313	0.487	0.535	
MH1-DGA	Domestic	95.56	100	0.188	0.002	0.563	0.534
	Downstream	95.56	99.6	0.188	0.105	0.543	
	Irrigation	95.28	98.46	0.235	0.333	0.531	
MH2-SGA	Domestic	79.17	99.8	0.227	0.011	0.562	0.542
	Downstream	79.17	99.47	0.227	0.027	0.559	
	Irrigation	78.89	97.52	0.224	0.126	0.536	
MH2-DGA	Domestic	77.5	99.98	0.235	0.001	0.566	0.532
	Downstream	77.22	99.54	0.22	0.022	0.549	
	Irrigation	76.94	98.33	0.205	0.076	0.526	

5.4.4 Summary

This study has developed optimal hedging policies integrated the optimal rule curves (i.e. SGA and DGA) obtained from the section 5.3.2.3. The decision variables, i.e. the set of monthly storages defining the critical rule curve that triggers rationing and the rationing ratio, were optimised by SGA and DGA. Two objective functions were used to compare the results of the hedging policy: the minimising of the sum square of period shortages (SS) and the minimising of the modified shortage index (MSI).

In terms of the total amount of water released over the 360 months of the simulation, the optimal rule curves without hedging rules were better than all the derived hedging policies; however, this has masked incidences of large single period shortages (vulnerability) with no hedging policy. The vulnerability (η) was reduced by using the optimised hedging rules, especially η for the high priority demand sector (i.e. domestic) was significantly reduced when using the objective function of MSI. This is because this objective function provided the individual rationing ratio for each demand sector. This situation highlights the benefit of water saving during normal reservoir operation because it can bring about a significant reduction in the impacts (or vulnerability) of water shortage.

A reduction in the number and amount of large single-period shortages often comes at the expense of a higher number of periods of moderate and small water shortages, and this is no exception in the current study. For example as the number of occasions of shortages was increased for the hedging policies. This has in turn affected to reduce the time-based reliability, R_t. However, this should not be a source of concern since in terms of water availability as characterised by the volumetric reliability, R_v, the systems performance is still acceptable i.e. R_v for the high priority demand sector (domestic and in-stream) was higher than 99% and for the lowest priority (irrigation) was higher than 97%.

5.5 Inflow forecasting using ANN for reservoir operation

5.5.1 Introduction

All the reported simulations hitherto have assumed that the total amount of available water for allocation (=starting storage + expected inflow) is known at the start of the period. In fact, the assumption was that the expected inflow was equal to the historic runoff for the month under consideration. In practice, this is not so and various ways of providing estimates of the expected inflow must be devised, each with implications for the operation performance of the reservoir. In the study, the use of ANN (see section 3.6) for inflow forecasting was adopted and its effect was compared to other inflow knowledge simulations:

(1) inflow is known and assumed to be the historic (Type A)

(2) inflow is known and assumed to be the ANN forecast (Type F)

(3) inflow is known and assumed to be the historic average for the given month (Type M)

(4) inflow is not known and the release decision is conditioned only the starting reservoir storage (Type N)

5.5.2 ANN inflow forecasts

Based on extensive testing involving the examination of the auto-correlation function (acf), partial-autocorrelation (pcf) and cross-correlation function (ccf), the different combinations of input variables were tested for the ANN modelling in follows, as seen in Figure 5.12 (a), (b) and (c). The acf (Figure 5.11 (a)) shows infinite attenuation with only the first three lags of inflow being significant. The pcf (Figure 5.11 (b)) shows alternatively positive and negative decrease in the partial correlation, the first and tenth lags being significant. Both the acf and pcf indicate the first lag as being the most significant where the maximum acf and pcf of inflow is 0.4227 statistically significant at 95% confidence level. The second lag of pcf is 0.093 almost higher than 95% confidence (0.104); however, it is one of significant lags in the acf. Additionally, the ccf in Figure 5.11 (c) indicates that the first two lags of the rainfall are 0.381 and 0.197, respectively statistically significant at 95% confidence level. With these, functional forms of the tested forecast models become:

$$\text{Model 1: } Q_t = f(Q_{t-1}, Q_{t-2}, Q_{t-3}, R_{t-1}, R_{t-2}) \tag{5.1}$$

$$\text{Model 2: } Q_t = f(Q_{t-1}, Q_{t-2}, Q_{t-3}, R_{t-1}) \tag{5.2}$$

$$\text{Model 3: } Q_t = f(Q_{t-1}, Q_{t-2}, R_{t-1}, R_{t-2}) \tag{5.3}$$

$$\text{Model 4: } Q_t = f(Q_{t-1}, Q_{t-2}, R_{t-1}) \tag{5.4}$$

$$\text{Model 5: } Q_t = f(Q_{t-1}, R_{t-1}) \tag{5.5}$$

$$\text{Model 6: } Q_t = f(Q_{t-1}, Q_{t-2}, Q_{t-3}, R_{t-1}, R_{t-2}, \overline{Q}_t) \tag{5.6}$$

$$\text{Model 7: } Q_t = f(Q_{t-1}, Q_{t-2}, Q_{t-3}, R_{t-1}, \overline{Q}_t) \tag{5.7}$$

$$\text{Model 8: } Q_t = f(Q_{t-1}, Q_{t-2}, R_{t-1}, R_{t-2}, \overline{Q}_t) \tag{5.8}$$

$$\text{Model 9: } Q_t = f(Q_{t-1}, Q_{t-2}, R_{t-1}, \overline{Q}_t) \tag{5.9}$$

$$\text{Model 10: } Q_t = f(Q_{t-1}, R_{t-1}, \overline{Q}_t) \tag{5.10}$$

where Q_t is the one-month ahead inflow forecast; Q_{t-1}, Q_{t-2} and Q_{t-3} are lagged inflows of one-month, two-month and three-month, respectively; R_{t-1} and R_{t-2} are lagged rainfall of one-month, two-month, respectively; $\overline{Q}_t$ is historic mean inflow for the current month.

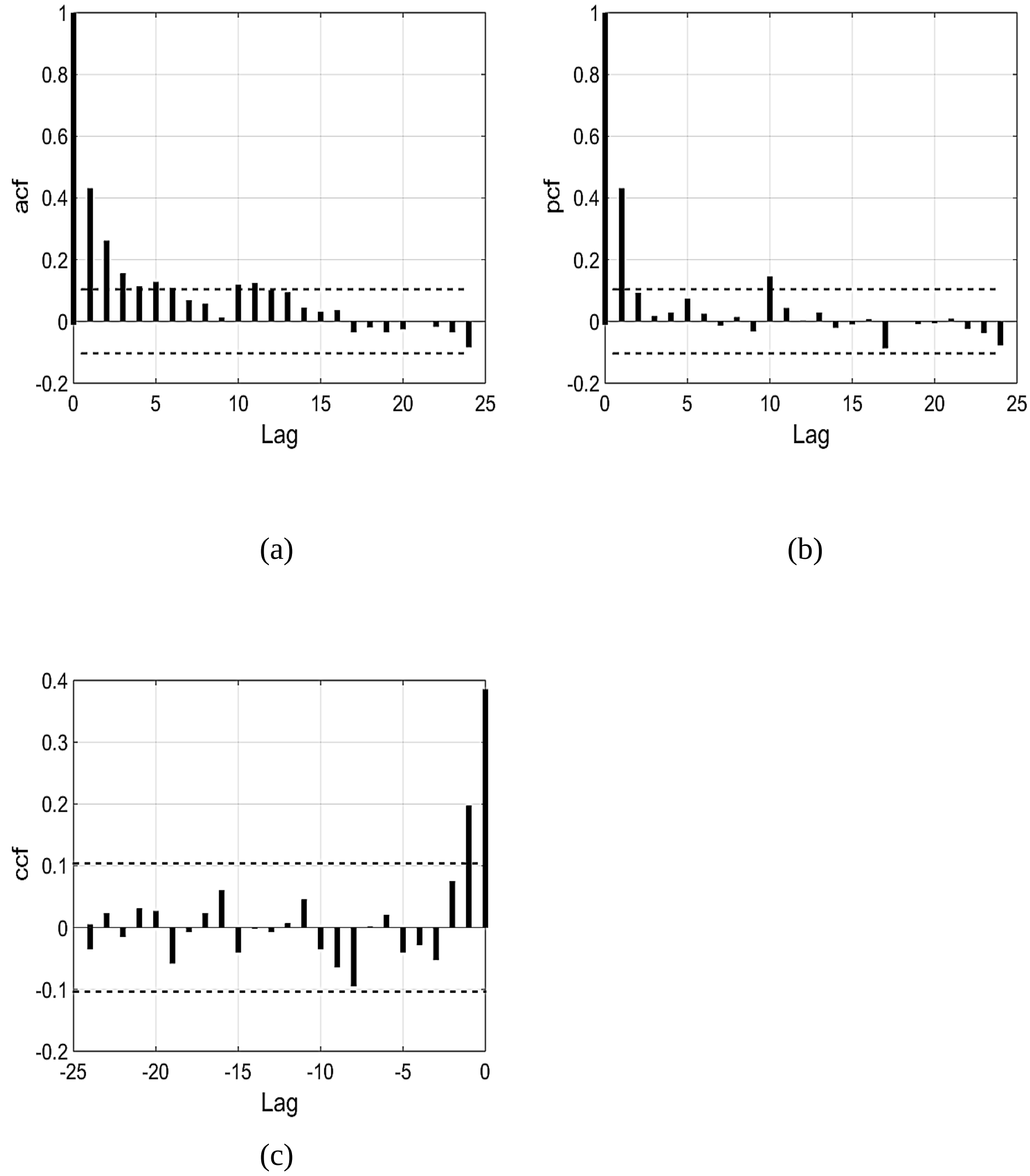


Figure 5.11 Inflow (a) auto-correlation, (b) partial autocorrelation functions, and (c) inflow-rainfall cross-correlation function for Ubonratana system

The early-stop-rule (ESR) was used for the ANN training for this 360 months (April 1982 to March 2012) of data were split into three (90:5:5) for training, validation and testing, respectively. The number of hidden neurons was varied between 1 and 35 and based on the *R* criterion. The best performance based on the *R* criterion in validation of each model over 10 runs was selected as seen in Table 5.22. Each time a neural network is trained, this can result in a different solution due to the different initial weight and bias values and different random data points of training, validation, and test sets. Based on the *R* criterion the best architecture is Model 6 had 33 neurons in the hidden layer, the model performed well with the *R* exceeding 0.9 in each of the training, validation and testing. The performance plot shows the value of the performance function versus the iteration number, as seen in Figure 5.12.

As seen in Figure 5.12, the training continued for 6 more iterations to 22 epochs before the training stopped to ensure the best performance of validation. The validation and test curves are similar, so the learning with back-propagation algorithm does not indicate any major problems with the training. If the test curve had increased significantly before the validation curve increased, then it is possible that some overfitting might have occurred. Consequently, in these cases no significant overfitting has occurred by iteration 16 (where the best validation performance occurs).

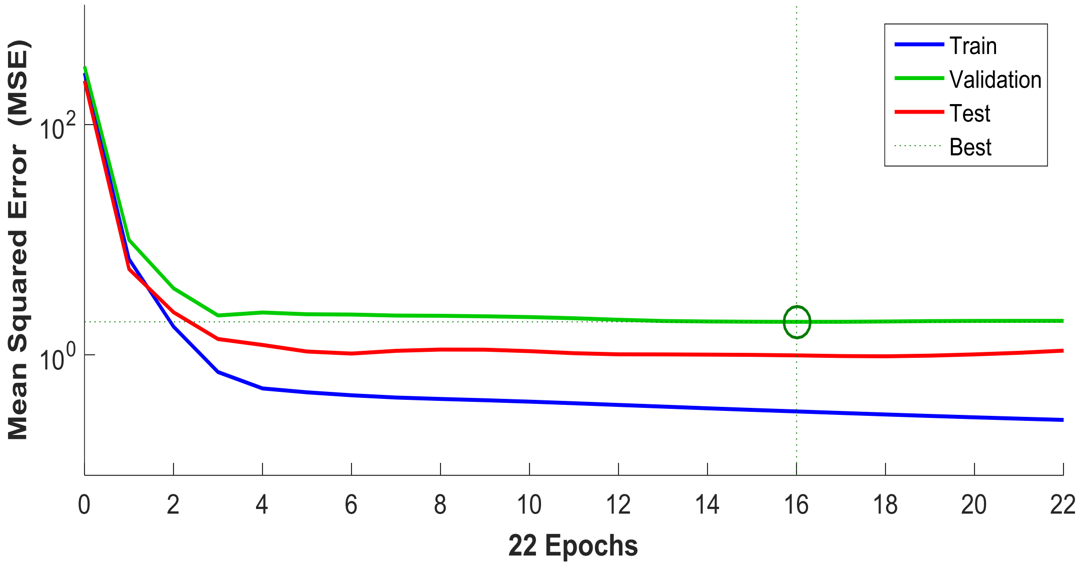


Figure 5.12 The best validation performance reached for Model 6 with 33 hidden neurons

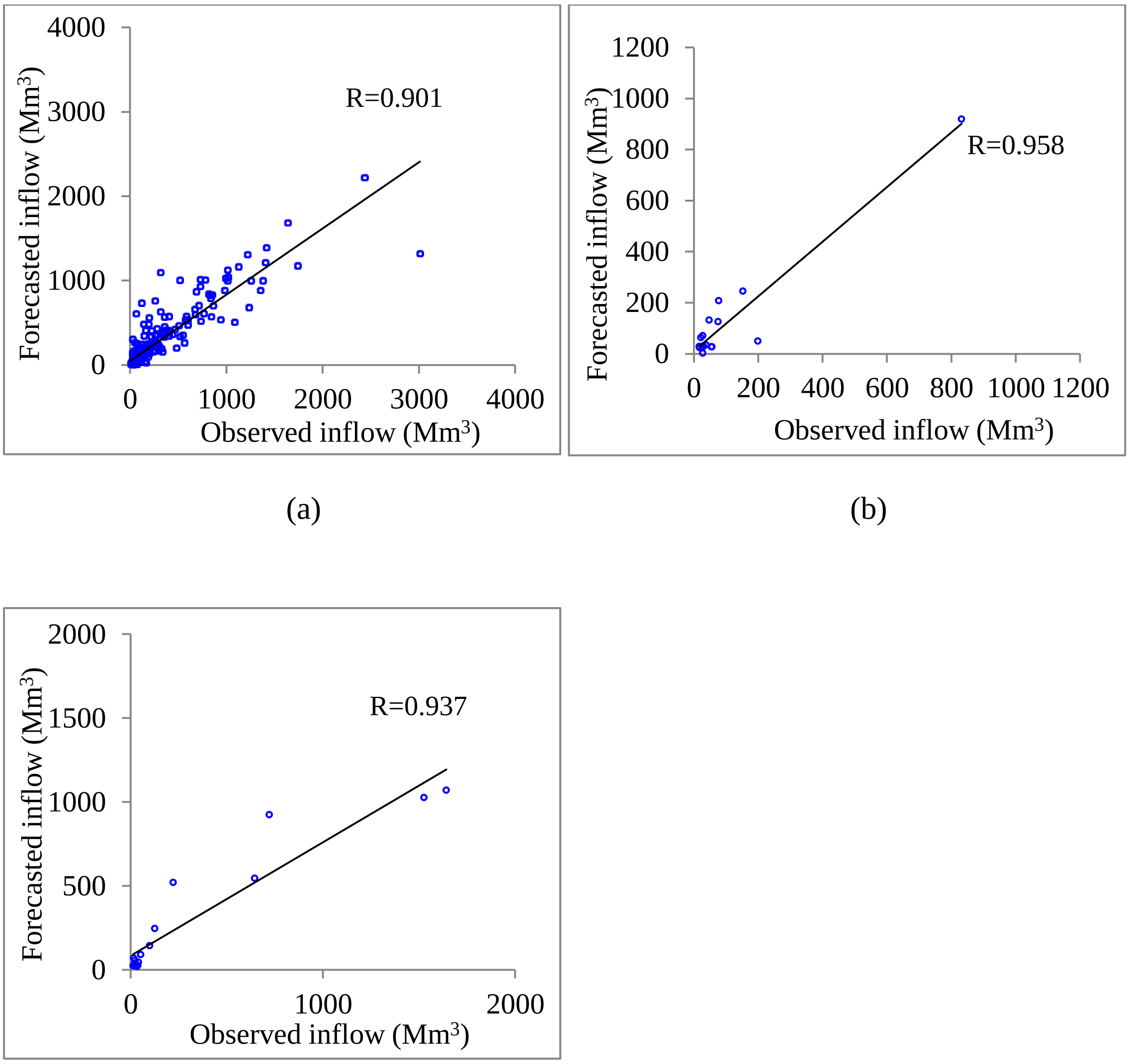
Table 5.22 The best performance over 10 runs of each model based on the R criterion

Hidden	Model 1			Model 2			Model 3			Model 4			Model 5		
neuron	Training	Validation	Testing	Training	Validation	Testing	Training	Validation	Testing	Training	Validation	Testing	Training	Validation	Testing
1	0.727	0.96	0.602	0.721	0.947	0.899	0.703	0.967	0.812	0.698	0.972	0.867	0.726	0.956	0.675
2	0.726	0.898	0.809	0.718	0.942	0.959	0.729	0.978	0.846	0.752	0.96	0.623	0.718	0.983	0.982
3	0.724	0.961	0.628	0.741	0.898	0.748	0.732	0.915	0.695	0.715	0.913	0.789	0.731	0.902	0.717
4	0.724	0.981	0.74	0.727	0.938	0.872	0.765	0.978	0.725	0.728	0.975	0.71	0.693	0.912	0.943
5	0.761	0.97	0.762	0.75	0.939	0.61	0.743	0.966	0.559	0.749	0.994	0.491	0.741	0.973	0.847
6	0.746	0.943	0.724	0.558	0.945	0.405	0.729	0.974	0.904	0.725	0.954	0.921	0.681	0.938	0.84
7	0.76	0.939	0.893	0.739	0.972	0.618	0.72	0.99	0.925	0.743	0.978	0.873	0.743	0.931	0.908
8	0.765	0.93	0.875	0.753	0.986	0.744	0.761	0.981	0.815	0.75	0.972	0.562	0.733	0.921	0.832
9	0.739	0.984	0.613	0.736	0.991	0.642	0.755	0.959	0.935	0.767	0.966	0.679	0.728	0.947	0.841
10	0.751	0.946	0.774	0.738	0.96	0.931	0.731	0.922	0.885	0.7	0.962	0.86	0.71	0.929	0.546
11	0.692	0.938	0.272	0.711	0.912	0.77	0.769	0.952	0.54	0.738	0.951	0.84	0.734	0.923	0.766
12	0.765	0.939	0.774	0.741	0.977	0.485	0.788	0.927	0.313	0.739	0.99	0.849	0.74	0.969	0.906
13	0.729	0.906	0.812	0.764	0.901	0.899	0.747	0.942	0.955	0.692	0.95	0.551	0.751	0.941	0.655
14	0.755	0.962	0.825	0.754	0.914	0.868	0.702	0.985	0.854	0.692	0.993	0.7	0.67	0.977	0.847
15	0.779	0.925	0.846	0.72	0.986	0.951	0.798	0.985	0.639	0.757	0.918	0.739	0.691	0.976	0.93
16	0.619	0.979	0.469	0.755	0.903	0.917	0.582	0.921	0.809	0.748	0.904	0.966	0.774	0.964	0.921
17	0.749	0.94	0.9	0.774	0.924	0.683	0.751	0.975	0.551	0.785	0.957	0.577	0.737	0.965	0.897
18	0.785	0.942	0.537	0.762	0.898	0.652	0.76	0.833	0.898	0.719	0.991	0.883	0.734	0.928	0.798
19	0.749	0.96	0.395	0.737	0.96	0.682	0.618	0.929	0.647	0.68	0.939	0.496	0.751	0.937	0.941
20	0.748	0.977	0.797	0.715	0.977	0.642	0.736	0.887	0.884	0.784	0.911	0.777	0.775	0.97	0.407
21	0.758	0.957	0.577	0.797	0.952	0.796	0.749	0.902	0.578	0.735	0.992	0.455	0.744	0.953	0.785
22	0.749	0.912	0.812	0.792	0.946	0.624	0.775	0.974	0.901	0.755	0.953	0.568	0.649	0.992	0.666
23	0.8	0.974	0.977	0.763	0.898	0.6	0.743	0.963	0.799	0.679	0.878	0.722	0.764	0.887	0.887
24	0.763	0.977	0.885	0.649	0.946	0.54	0.689	0.93	0.784	0.748	0.913	0.905	0.746	0.965	0.779
25	0.783	0.95	0.626	0.781	0.909	0.32	0.748	0.91	0.784	0.775	0.845	0.751	0.718	0.917	0.935
26	0.811	0.845	0.418	0.796	0.933	0.77	0.754	0.951	0.939	0.751	0.928	0.671	0.691	0.933	0.63
27	0.772	0.926	0.675	0.76	0.955	0.747	0.812	0.889	0.599	0.75	0.971	0.559	0.744	0.987	0.62
28	0.771	0.94	0.934	0.762	0.953	0.681	0.75	0.987	0.807	0.621	0.925	0.458	0.739	0.982	0.534
29	0.777	0.943	0.753	0.735	0.912	0.496	0.805	0.974	0.856	0.754	0.877	0.742	0.766	0.98	0.82
30	0.697	0.962	0.799	0.746	0.97	0.929	0.712	0.955	0.46	0.756	0.864	0.68	0.748	0.958	0.818
31	0.781	0.978	0.659	0.765	0.9	0.692	0.78	0.934	0.94	0.784	0.976	0.549	0.712	0.929	0.806
32	0.803	0.953	0.502	0.779	0.857	0.949	0.768	0.892	0.675	0.747	0.992	0.837	0.773	0.896	0.524
33	0.739	0.966	0.67	0.766	0.976	0.272	0.8	0.988	0.763	0.73	0.943	0.827	0.753	0.955	0.913
34	0.667	0.955	0.757	0.763	0.93	0.752	0.797	0.911	0.784	0.746	0.938	0.725	0.7	0.978	0.729
35	0.806	0.941	0.638	0.721	0.839	0.571	0.776	0.93	0.78	0.787	0.909	0.947	0.778	0.851	0.556

Table 5.22 The best performance over 10 runs of each model based on the R criterion (Continued)

Hidden	Model 6			Model 7			Model 8			Model 9			Model 10		
neuron	Training	Validation	Testing	Training	Validation	Testing	Training	Validation	Testing	Training	Validation	Testing	Training	Validation	Testing
1	0.699	0.894	0.821	0.766	0.903	0.799	0.724	0.941	0.791	0.719	0.898	0.974	0.722	0.942	0.946
2	0.704	0.962	0.851	0.684	0.982	0.839	0.722	0.971	0.956	0.739	0.925	0.762	0.722	0.972	0.828
3	0.721	0.983	0.815	0.653	0.965	0.749	0.709	0.955	0.892	0.75	0.96	0.869	0.752	0.892	0.432
4	0.724	0.889	0.899	0.746	0.93	0.614	0.766	0.981	0.814	0.698	0.985	0.794	0.722	0.909	0.931
5	0.72	0.905	0.732	0.714	0.941	0.73	0.737	0.946	0.778	0.703	0.945	0.909	0.734	0.957	0.785
6	0.752	0.962	0.511	0.754	0.949	0.731	0.731	0.938	0.735	0.741	0.966	0.767	0.718	0.993	0.377
7	0.708	0.981	0.496	0.786	0.98	0.725	0.74	0.956	0.756	0.74	0.984	0.655	0.74	0.932	0.931
8	0.761	0.953	0.815	0.808	0.959	0.212	0.777	0.971	0.575	0.756	0.899	0.884	0.724	0.953	0.805
9	0.642	0.92	0.907	0.765	0.976	0.431	0.76	0.994	0.776	0.737	0.922	0.91	0.779	0.957	0.646
10	0.824	0.994	0.77	0.784	0.959	0.748	0.76	0.922	0.754	0.828	0.951	0.866	0.748	0.975	0.373
11	0.777	0.945	0.742	0.798	0.91	0.816	0.834	0.913	0.684	0.727	0.98	0.8	0.736	0.908	0.825
12	0.795	0.962	0.48	0.75	0.913	0.924	0.789	0.919	0.48	0.805	0.981	0.565	0.763	0.945	0.601
13	0.768	0.947	0.657	0.758	0.95	0.853	0.787	0.943	0.526	0.638	0.984	0.955	0.75	0.975	0.944
14	0.763	0.873	0.868	0.687	0.992	0.775	0.717	0.978	0.868	0.629	0.941	0.554	0.769	0.926	0.932
15	0.73	0.921	0.684	0.806	0.969	0.695	0.764	0.931	0.717	0.779	0.956	0.563	0.74	0.964	0.876
16	0.901	0.966	0.543	0.781	0.985	0.855	0.85	0.956	0.562	0.768	0.861	0.773	0.752	0.953	0.841
17	0.786	0.975	0.91	0.855	0.948	0.577	0.655	0.985	0.805	0.734	0.989	0.756	0.766	0.962	0.808
18	0.814	0.954	0.876	0.837	0.924	0.83	0.804	0.9	0.737	0.76	0.931	0.784	0.758	0.964	0.649
19	0.835	0.994	0.72	0.781	0.898	0.936	0.64	0.98	0.288	0.791	0.91	0.609	0.702	0.953	0.335
20	0.808	0.944	0.862	0.821	0.922	0.507	0.776	0.898	0.742	0.803	0.963	0.671	0.741	0.983	0.83
21	0.735	0.959	0.464	0.813	0.935	0.513	0.772	0.921	0.886	0.828	0.968	0.707	0.743	0.938	0.681
22	0.787	0.97	0.726	0.834	0.93	0.706	0.756	0.936	0.879	0.73	0.955	0.629	0.765	0.898	0.888
23	0.739	0.885	0.762	0.776	0.939	0.4	0.816	0.924	0.873	0.787	0.963	0.914	0.631	0.947	0.61
24	0.827	0.907	0.876	0.802	0.92	0.483	0.795	0.961	0.81	0.783	0.981	0.568	0.701	0.927	0.737
25	0.89	0.918	0.639	0.869	0.939	0.593	0.854	0.97	0.864	0.83	0.987	0.8	0.683	0.894	0.499
26	0.834	0.92	0.823	0.813	0.964	0.649	0.659	0.942	0.678	0.808	0.949	0.034	0.781	0.918	0.574
27	0.666	0.975	0.88	0.841	0.947	0.394	0.768	0.897	0.705	0.871	0.988	0.911	0.776	0.955	0.568
28	0.832	0.945	0.769	0.855	0.965	0.701	0.703	0.948	0.858	0.795	0.973	0.711	0.769	0.952	0.882
29	0.817	0.972	0.637	0.872	0.968	0.673	0.847	0.961	0.984	0.811	0.977	0.758	0.797	0.909	0.873
30	0.812	0.967	0.718	0.71	0.865	0.635	0.859	0.973	0.82	0.869	0.952	0.677	0.731	0.978	0.71
31	0.86	0.906	0.567	0.796	0.954	0.587	0.805	0.941	0.859	0.809	0.975	0.67	0.764	0.938	0.915
32	0.92	0.979	0.143	0.782	0.85	0.667	0.791	0.97	0.81	0.858	0.953	0.286	0.72	0.97	0.763
33	0.901	0.958	0.937	0.859	0.91	0.903	0.773	0.994	0.863	0.769	0.958	0.576	0.798	0.847	0.46
34	0.853	0.972	0.8	0.824	0.989	0.477	0.564	0.923	0.33	0.749	0.989	0.821	0.772	0.952	0.854
35	0.856	0.966	0.934	0.821	0.913	0.741	0.846	0.975	0.862	0.83	0.912	0.954	0.828	0.991	0.657

The best validation performance (MSE) after post-processing is 3,964, and the performance of training and testing are 25,706 and 41,777, respectively. Figure 5.13 (a), (b) and (c) compare the predicted and observed inflow during training, validation and testing, respectively and further confirm the good performance of the forecasting model. The solid line represents the best fit linear regression line between outputs and targets. The *R* value is an indication of the relationship between the outputs and targets. If *R* = 1, this indicates that there is an exact linear relationship between outputs and targets. If *R* is close to zero, then there is no linear relationship between outputs and targets.



(c)

Figure 5.13 Comparing the 1-month ahead observed and forecast inflow during (a) training, (b) validation, and (c) testing

The time series of the forecast inflows (April 1982 to March 2012, i.e. 360 months) are also compared in Figure 5.14 and this together with the estimated Nash-Sutcliffe efficiency (NSE) of 0.75 is further evidence of the efficacy of the forecasting model. Additionally, the fact that the NSE was higher than zero is an indication that the model has been a better predictor than the mean value of the observed time series. As seen in Figure 5.14, the ANN was unable to capture the largest peak in September 2002. This is a problem with ANN and has been observed before in other studies, e.g. Sudheer et al., (2003) who attributed this to the local variations in the function being mapped due to varying skewness in the data series. A comforting feature of Figure 5.14 is that the model was very good in simulating the low flows in the historic record, which is more important for the main water resources issue addressed by the study.

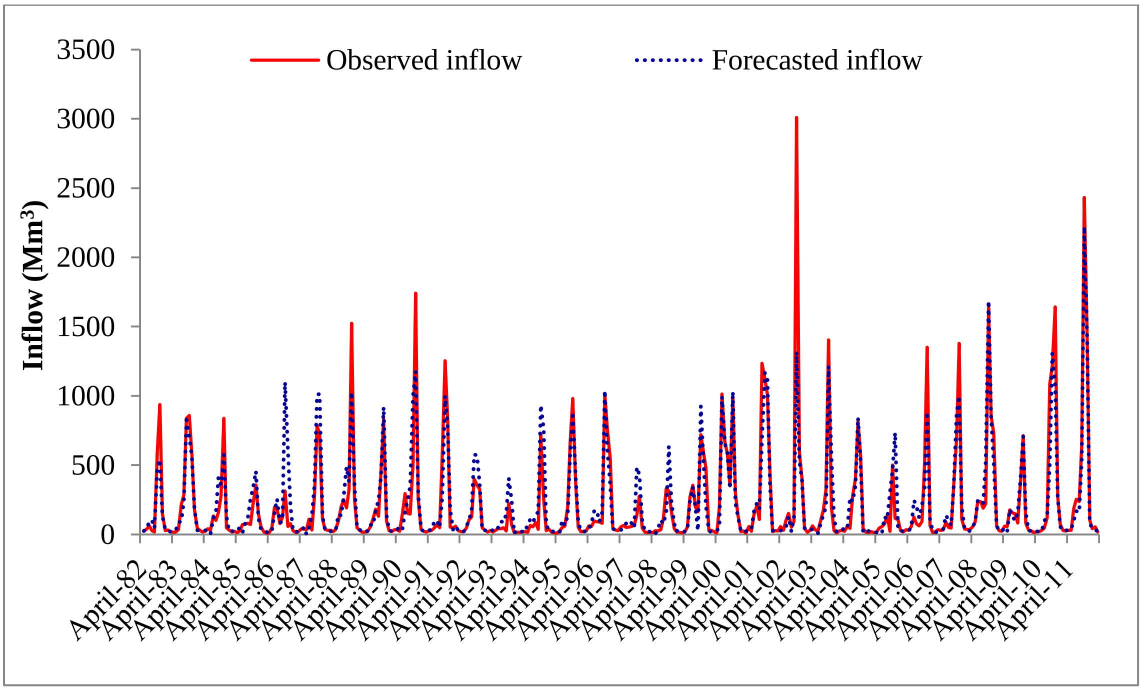


Figure 5.14 Time series of one-month ahead of observed and forecast inflows for the complete data record

5.5.3 Performance evaluation for the rule curves

The results of the performance evaluation of the rule curves are summarised in Table 5.23. For convenience, the operating policy (i.e. the optimised rule curves by DGA in section 5.3.2.3) with Type A, Type F, Type M and Type N are denoted by P-A, P-F, P-M and P-N, respectively. As seen in Table 5.23, in terms of the total amount of water released, P-A, P-F and P-M were significantly better than P-N, which is not surprising given that P-N did not have any additional water from inflows. In term of the total amount of water shortage over 360 months of the simulation, P-A (=310 Mm^3) was 26.8% and 85.9% higher than P-F (=244.5 Mm^3) and P-M (=166.8 Mm^3), respectively. In terms of reliability (R_t and R_v), the P-F was marginally better than using P-A and significantly better than P-N; P-F was, however, inferior to P-M. A possible reason for this is that in some of the months, the historic monthly mean and forecast inflows were higher than the actual inflows, implying that more water will be released in those months with P-M and P-F than with the other two inflow situations.

However, the net effect of such large releases (based on the upwardly-biased inflow forecasts) is the increased number of excursions of the end-of-period storage ($S_{end,t}$) into the region below the LRC as shown in Table 5.23 for both the P-F and P-M. The other performance indices reported in Table 5.23 all reveal the superiority of P-F relative to the other inflow situations. For example, the group sustainability index for P-F was the highest of all four; indeed, the same better performance of P-F was recorded across all three (public, instream and irrigation) demand sectors supplied by the reservoir. As expected, the conservative nature of P-N resulted in the least number of excursions below the LRC. This is likely to benefit the hydropower generation potential of the reservoir albeit, as revealed by this study, at the expense of its performance in meeting the consumptive demands.

Table 5.23 Summary of evaluated reservoir performance indices for the rule curve

Policy	Water user	Total water shortage (Mm3)	End storage<LRC	f_d	f_s	Reliability (%)		φ	η	λ_{user}	λ_G
						R_t	R_v				
P-A	Domestic	0.000	8	0	0	100.00	100.00	-	0.000	1.000	0.619
	Downstream	0.497		1	1	99.72	99.99	1	0.026	0.990	
	Irrigation	309.4		15	3	95.83	98.58	0.200	0.357	0.498	
	Total	309.9									
P-F	Domestic	0.000	14	0	0	100.00	100.00	-	0.000	1.000	0.704
	Downstream	0.000		0	0	100.00	100.00	-	0.000	1.000	
	Irrigation	244.5		10	4	97.22	98.88	0.400	0.426	0.607	
	Total	244.5									
P-M	Domestic	0.000	16	0	0	100.00	100.00	-	0.000	1.000	0.593
	Downstream	0.000		0	0	100.00	100.00	-	0.000	1.000	
	Irrigation	166.8		6	1	98.33	99.24	0.167	0.407	0.460	
	Total	166.8									
P-N	Domestic	3.228	4	6	5	98.33	99.09	0.833	1.000	0.000	0.580
	Downstream	132.7		10	9	97.22	98.04	0.900	0.793	0.566	
	Irrigation	1062.6		28	15	92.22	95.13	0.536	0.576	0.594	
	Total	1198.5									

5.5.4 Performance evaluation for the hedging policies

The results of the performance evaluation of the single- and two-stage hedging policies are summarised in Table 5.24 and Table 5.25, respectively. For convenience, the hedging policies (i.e. the optimised hedging MH1-DGA and MH2-DGA in section 5.4.3) with Type A, Type F, Type M and Type N are denoted by H1-A, H1-F, H1-M and H1-N for the single-stage hedging, respectively, and by H2-A, H2-F, H2-M and H2-N for the two-stage hedging, respectively. As seen in Table 5.24 and 5.25, in terms of the total amount of water released, H1-A, H1-F and H1-M were significantly better than H1-N similar to H2-A, H2-F and H2-M were significantly better than H2-N.

As seen in Table 5.24, in terms of the total amount of water shortage over 360 months of the simulation, H1-A (=363.2 Mm^3) was 30% and 72% higher than H1-F (=299.7 Mm^3) and H1-M (=211.4 Mm^3), respectively. H2-M is also better than H2-A and H2-F in terms of the total shortage in two-stage hedging, as seen in Table 5.25. In terms of reliability (R_t and R_v), the H1-F was marginally better than using H1-A, and significantly better than H1-N. Similarly, H2-F was marginally better than using H2-A, and significantly better than H2-N. H1-M was better than H1-F and H2-M was better than H2-F in terms of R_t and R_v, as expected. The possible reason of this situation has already been discussed in the previous section. The large releases with H1-M resulted in higher number of occurrences of S_{end} <LRC (=14) than H1-A (=7) and H1-F (=11), as seen in Table 5.24. However, the occurrence of S_{end} <LRC was 0 for H1-N (see Table 5.24) and 1 for H2-N (see Table 5.25) because of no large releases since the available water was restricted to the starting period storage.

The other performance indices reported in Table 5.25 all reveal the superiority of M2-F relative to the other inflow situations. For example, the group sustainability index for M2-F was the highest of all four. In terms of the group sustainability index for M1-F was better than M1-A and M1-M, but it was inferior to M1-N because M1-N has higher resilience (φ). However, other performance indices as seen in Table 2.54 of M1-F were superior to M1-N.

Table 5.24 Summary of evaluated reservoir performance indices for the single-stage hedging

Policy	Water user	Total water shortage (Mm^3)	End storage<LRC	f_d	f_s	Reliability (%)		φ	η	λ_{user}	λ_G
						R_t	R_v				
H1-A	Domestic	0.009	7	16	3	95.56	100.00	0.188	0.002	0.563	0.534
	Downstream	27.0		16	3	95.56	99.60	0.188	0.105	0.543	
	Irrigation	336.2		17	4	95.28	98.46	0.235	0.333	0.531	
	Total	363.2									
H1-F	Domestic	0.006	11	11	4	96.94	100.00	0.364	0.002	0.706	0.628
	Downstream	19.9		11	4	96.94	99.71	0.364	0.105	0.681	
	Irrigation	279.8		13	5	96.39	98.72	0.385	0.388	0.610	
	Total	299.7									
H1-M	Domestic	0.004	14	8	2	97.78	100.00	0.250	0.002	0.625	0.545
	Downstream	14.2		8	2	97.78	99.79	0.250	0.105	0.603	
	Irrigation	197.2		8	2	97.78	99.10	0.250	0.404	0.526	
	Total	211.4									
H1-N	Domestic	3.287	0	44	32	87.78	99.07	0.727	0.138	0.819	0.704
	Downstream	185.1		44	32	87.78	97.27	0.727	0.251	0.782	
	Irrigation	1495.5		48	32	86.67	93.15	0.667	0.462	0.677	
	Total	1683.9									

Table 5.25 Summary of evaluated reservoir performance indices for the two-stage hedging

Policy	Water user	Total water shortage (Mm^3)	End storage <LRC	f_d	f_s	Reliability (%)		φ	η	λ_{user}	λ_G
						R_t	R_v				
H2-A	Domestic	0.067	7	81	15	77.50	99.98	0.185	0.001	0.523	0.524
	Downstream	30.9		82	15	77.22	99.54	0.183	0.022	0.517	
	Irrigation	364.7		83	17	76.94	98.33	0.205	0.076	0.526	
	Total	395.7									
H2-F	Domestic	0.054	13	71	20	80.28	99.98	0.282	0.001	0.609	0.599
	Downstream	24.0		71	20	80.28	99.65	0.282	0.021	0.605	
	Irrigation	306.3		76	22	78.89	98.60	0.289	0.069	0.597	
	Total	330.4									
H2-M	Domestic	0.039	14	49	15	86.39	99.99	0.306	0.001	0.642	0.592
	Downstream	13.4		49	14	86.39	99.80	0.286	0.015	0.624	
	Irrigation	235.7		56	14	84.44	98.92	0.250	0.069	0.581	
	Total	249.1									
H2-N	Domestic	3.366	1	142	35	60.56	99.05	0.246	0.043	0.523	0.506
	Downstream	158.3		142	35	60.56	97.66	0.246	0.067	0.518	
	Irrigation	1226.9		144	35	60.00	94.38	0.243	0.131	0.502	
	Total	1388.6									

5.5.5 Summary

This study has developed MLP-ANN model to forecast one-month-ahead inflow for the Ubonratana reservoir. Based on the *R* criterion of tested models, the best architecture has six input variables (i.e. current month historic mean inflow, lagged inflow (t-1, t-2, t-3), and lagged rainfall (t-1, t-2)) and 33 neurons in hidden layer. Extensive testing of the model showed that it was able to provide inflow forecasts with reasonable accuracy with the *R* is 0.901 for training, 0.958 for validation and 0.937 for testing. The performance of the ANN forecasts was tested against those three other inflow scenarios and the reservoir simulation results showed that the ANN forecasts produced superior reservoir performance. The worst performing inflow situation was when there was complete lack of knowledge about the inflow and release decision was based on the starting storage alone. All this represents an objective demonstration of good inflow forecast knowledge for effective reservoir operation.

5.6 Summary

In this chapter, the performance of existing rule curves (i.e. pre-2002 and post-2002), proposed rule curves by Chiamsathit et al. (2014a) and SOP were evaluated in section 5.2. The results show that the vulnerability of the existing policies was quite high (i.e. large single period shortages). Therefore, the existing policies were developed by using optimization of rule curves integrated with hedging policies. The optimal rule curves for the reservoir operation were obtained using the standard GA (SGA) and dynamic GA (DGA) optimization in section 5.3.2. To test the accuracy of GA, the results of the optimised rule curves with NLP were compared to the optimized rule curves with GA in section 5.3.3. The reservoir policies were developed by integrating the optimised rule curves with two types of optimised hedging policies i.e. single-stage and two-stage hedging policies in section 5.4. The use of ANN for one-month-ahead inflow forecasts were demonstrated, resulting reasonable accuracy in section 5.5.2. To access how well the forecast inflows have performed in the operation of the reservoir, simulations were carried out guided by the policies (i.e. the optimal rule curves, the single-stage and the two-stage hedging policies) in section 5.5.3 and 5.5.4.

Chapter 6 Discussion of Results and Limitations of the Study

6.1 Discussion of results

6.1.1 Development of reservoir operation policy using reservoir simulation model

The initial set of rule curves (P1) used for the operation of the Ubonratana prior to 2002 performed the water supply function satisfactorily but failed on flooding. The post-2002 rules (P2) that replaced them reduced the flooding problem but aggravated water shortage. Chiamsathit et al. (2014) has developed a new set of rule curves (P3) that has remedied the post-2002 water shortage problem. The performance of the three operating policies along with the SOP in meeting water demands was compared using the reliability index, which was evaluated for each of three user categories, namely domestic, downstream and irrigation needs, and for an aggregation of the categories. While the SOP was the best for water supply, it is not a realistic option for reservoir operation when flood control is a consideration because reservoir storage can attain the maximum full capacity level with the SOP, with little or no space left in the reservoir for accommodating flood water. Of the three heuristic rules evaluated, the reliability results showed that P3 was better than both P1 and P2, for the individual categories.

Although the lower rule curve for P3 was much lower than its P1 and P2 counterparts, statistical analysis carried out to establish the probability of reservoir storage ever reaching the minimum pool level with P3 showed that this is very low. This is a significant outcome because maintaining water above the minimum pool level at Ubonratana is important to guarantee adequate hydropower generation. Finally, based on the limited consideration of hydropower generation in the study, P3 appears to be the best of the non-SOP policies. The better hydropower generation performance of the SOP (P4) relative to the others is to be expected but, as noted before, this would likely be at the expense of the additional flood protection that policies P1–P3 offer.

However, the reservoir performances in terms of the vulnerability showed that P3 was not significantly better than both P2 and P1. The vulnerability should be improved to decrease the volume of single period shortages. Therefore, the optimisation approach is required to improve the performance of reservoir rule curves, P3. Improvement in the P3 used the SGA and DGA in order to generate the optimised rule curves and the optimised hedging policies in section 5.3 and 5.4 respectively.

6.1.2 Optimisation of reservoir operating rule curves

In order to develop the reservoir operating rule curves, the genetic algorithm (GA) optimisation was applied. The key parameters of SGA and DGA were investigated. It was found that a population size of 200 and 1500 generations are the best combination for SGA. For DGA, generation =2 and repetition =7 represent the best combination. Comparing the performance of the reservoir when operated with the rule curves optimised using SGA and DGA showed that the DGA curves were far superior to the SGA curves. The optimised rule curves using DGA is superior to P3 in terms of vulnerability in all demand sectors. In particular, the evaluated sustainability indices showed that the DGA was better than the SGA and P3, for the individual water supply categories as well as their aggregation. A further attribute of the DGA is its speed at arriving at the global optimum. For example, recorded computational times for the DGA were on average about half of those required by a standard algorithm solving the same problem.

To test the accuracy of GA, the performance of the reservoir when it has been operated for a single year with the rule curves optimised using nonlinear programming (NLP) and GA showed that using GA was superior to NLP in the complex problem. For example, from the data on the lowest mean inflow in 1993, the reservoir performance of the optimised policy using SGA and DGA was better than using NLP. Additionally, in the longer period and with a more complex problem, NLP could not provide the feasible solution. However, the NLP optimisation works as well as GA in a simple problem, for example in the optimisation of the Ubonratana rule curves of the highest variable inflow in 2002. Using NLP and GA does not affect the simulation results of the optimised rule curves in the simple problem in 2002.

To benchmark the performance of DGA and SGA, the objective function of Shaffer's F7 was used. DGA is superior to SGA in finding the global optimal solution i.e. the percentages of reaching global optimum in DGA is 42.4% higher than SGA. The problem is that the initial constraints boundary of -100 to 100 might have been too wide relative to the global solution (i.e. 0, 0); thus the SGA was trapped in local optimum on numerous occasions. SGA may perform well by establishing the search space boundary close to the global optimum point. In real world problems, however, establishing the optimal boundary of the feasible region to search for the optimal solution is the main challenge because the global optimum is unknown. The SGA is unable to find the true search space, so this can cause the algorithm to miss the global optimum. The advantage of DGA is that it is insensitive to the initial bounds because it uses a modified search space reduction to update the new boundaries focusing around the optimal solution. Consequently, the average of the best fitness values over 100 runs for DGA was 0.00 which is the global optimum value; 94% were 0.00, while only 6 runs were 0.01.

6.1.3 Optimisation of hedging rules for development of reservoir operating policy

The optimised rule curves using SGA and DGA could improve vulnerability, but the full-unmet demand was found because the rule curves save no water for severe drought. Consequently, optimised hedging policies integrated with the rule curves were developed The significant feature of the reported work is that single-stage and two-stage hedging policies were developed using SGA and DGA to obtain the decision variables. The two objective functions for the optimisation were tested: (a) the minimising sum square of the period shortage (SS) and (b) the minimising modified shortage index (MSI). Subsequent reservoir simulations to test the effectiveness of the hedging rules show that significant reduction in the number of large single-period water shortages can be achieved by rationing, resulting in manageable vulnerability for the Ubonratana. Moreover, the number of large single-period water shortages was significantly reduced and no full-unmet demand was found by using the objective function of MSI.

To implement the SS objective function, a penalty structure is utilized by the Ubonratana operation procedure. When the storage level at the end of each month is less than the rule curve, some percentages of the irrigation demands and downstream requirements are not met in order to bring the storage level up to the curve. Domestic demands, however, are met as much as possible because they are the highest priority. This is different when the MSI is used as the objective function. For example, when the storage level at the end of each month is less than the rule curve, some percentage of all users' demands are not met in order to bring the storage level up to the curve. However, the amount of shortage for each user relies on its priority. The amount of water shortage for domestic demands is less than other users. Therefore, this strategy encourages the participation in sharing water shortage of all users in drought period.

It was found that the superiority of using MSI, was exemplified by the vulnerability for the downstream and irrigation water supply sectors. Therefore, using MSI for the objective function, the vulnerability of downstream and irrigation users were decreased. However, the superiority of using SS, is exemplified by the time-based reliability in high priority sectors (i.e. domestic and downstream sectors), but the volume-based reliability was not significantly affected. It was clear that using MSI benefits the reduction of the intensity of severe water shortages by rationing water supply for all demand sectors. As the hedging rules adjust water supply for impending droughts, the number of small shortages increases and thus the reliability of fully satisfying demands is reduced; this is also demonstrated by Taghian et. al., 2014. By using MSI for the objective function, therefore, in the drought period, all water sectors will participate in the water shortage. However, it is not suitable in a case where the water delivered is first aimed at satisfying the highest priority demand sector in full after which, if there is water left, attention turns to the lower priority demand sector and so on.

Reducing the number of large shortages caused the total number of failure periods to rise, leading to significant deterioration in the evaluated time-based reliability at the Ubonratana. However, since the amount of water shortages for most of these additional shortage periods was low to moderate, the overall volumetric reliability of the reservoir was practically acceptable. This is re-assuring since what should matter most in reservoir operation is not the number of failure occasions but the deficit sustained during such failures. It was found that the superiority of the two-stage hedging relative to single-stage hedging for both objective function (i.e. SS and MSI), is exemplified by the vulnerability. Therefore, in terms of the vulnerability, the two-stage hedging outperformed both the single-stage and no-hedging policies. Additionally, in term of the sustainability index, the single-stage and two-stage hedging are far superior to no-hedging policy (i.e. the optimal rule curves using SGA and P3).

Finally, although flood protection was not explicitly included in the rule-curves optimisation, none of the optimised hedging-integrated rules curves has encroached upon the area bounded by the existing flood curve at Ubontarana. This is to be expected given that in the optimisation solution, the upper boundary of the conservation upper rule curve was set to be below the flood rule curve. Thus the performance of the reservoir with regard to flood protection is not expected to be affected by the newly derived hedging-integrated rule curves.

6.1.4 Inflow forecasting coupled with the reservoir operating policies

In this study, multi-layer perceptron (MLP) ANN have been applied to forecast one-month-ahead inflow for the Ubonratana reservoir. Based on extensive testing involving the examination of the auto-correlation function, partial-auto correlation function and cross-correlation function, ten ANN models with different combination of input variables were formed and retained 10 times of each hidden neuron (varied between 1 and 35). The best architecture network contains six input variables with 33 hidden neurons which was highest accuracy ($R>0.9$ in each of training, validation and testing). The time series of the forecast inflows (April 1982-March 2012, i.e. 360 months) were used to test the effect of the forecast inflow on the performance of three operating policies: (1) the optimised rule curves, (2) one-stage hedging and (3) two-stage hedging.

As basis of comparison, four inflow situations were considered: (1) inflow is known and assumed to be the historic; (2) inflow is known and assumed to be the ANN forecast; (3) inflow is known and assumed to be the historic average for the given month; and (4) inflow is not known and the release decision is conditioned only the starting reservoir storage.

It was found that the forecast inflow situation for the optimised rule curves and two-stage hedging policy were more sustainable than other tested situations. More over using the forecast inflow for all tested polices was significantly better than an unknown inflow situation and marginally better than actual inflow situation in terms of R_v and R_t. However, in terms of the total amount of water shortage the forecast inflow situation was inferior to the historic average inflow situation. A possible reason of why the forecast inflow and the historic average inflow situation have less amount of water shortage was in some of months, inflows of these situations were higher than actual inflows, implying that more water will be released in those months than the actual inflow situation. However, the results of this releasing caused increasing of the occurrences of full-unmet demand. Therefore, the historic average inflow situation has highest number of occurrences of full-unmet demand.

It was found that the superiority of model with the situation of the forecast inflow relative to unknown inflow is exemplified by the total amount of water shortage, where the forecast inflow offers a system that is more than 50% less than that for unknown inflow. Therefore, the forecast inflow situation is clearly superior to the historic average and unknown inflow situation. Moreover, the forecast inflow situation produced the best performance while the unknown inflow situation was the worst performing. This clearly demonstrates the importance of good inflow information for effective reservoir operation.

6.1.5 Practical ramifications of hedging policy

Reservoirs play a key role in economic development, serving a variety of purposes, including electricity generation, flood control, and irrigation. For example, the Ubonratana dam reservoir provides about 2% of the total electricity demand in the chi river basin (EGAT, 2016). The dam also provides flood control services and water supplies for domestic, industry and agriculture. In periods of scarcity, all stakeholders participate in taking decisions on water allocation policy without any guidance about water rationing. Sharing a limited water resource by several stakeholders can create conflicts among them when their requirements exceed availability. More recently, it has been stressed that economic development should be compatible with political and social institutions (Nandalal and Simonovic, 2003). Therefore, a holistic concept of sustainable development has emerged in which economic, ecological, social, and political factors need to be simultaneously considered. Participation by individuals, particularly at the community level, is seen as an important means for achieving sustainable development and formulating development goals. In such situations, water allocation guided by the optimal hedging rules may ameliorate such conflicts.

As noted earlier, both the flooding and hydro-power functions of the reservoir were not optimised but, given the existence of a flood rule curve and the specification of a minimum water level for hydro-power generation, both functions are not expected to be degraded by their omission from the formal optimisation objective. Thus, it was not seen as inappropriate to restrict the objective function to a minimisation of the water deficit (and the modified water shortage index, MSI), which is also in tune with popular practice when consumptive water demands are the issue (Hsu and Cheng 2002). The evaluation of the performance of the reservoir following the optimisation considered all major indices, including the reliability (time-based and volume-based), resilience, vulnerability and sustainability but much focus was placed on the vulnerability in discussing the effect of hedging because it is the index that is most relevant to the water shortage objective function and hence large single-period water shortages. Obviously, there are possible trade-offs between these indices which make their use in water resources evaluation problematic, as noted by McMahon and Adeloye (2005). It is to avoid such trade-offs and the difficulties they pose for water resources decision-making that integrative indices (or figures of merit) such as the sustainability index were developed. Although the sustainability index was also evaluated in the study, it did not form the main discussion because, unlike the vulnerability, its link to actual water shortage would be difficult to readily appreciate especially by lay stakeholders. This is particularly so for farmers of paddy rice, whose cultivation is very prevalent in the region. Rice is a water intensive crop (Rajendren, 2006); consequently a water supply system such as the developed integrated hedging policy that guarantees limited shortfall should be preferred.

6.1.6 Scalability of the Methodology

Although the case study was a single reservoir system, the developed methodology is sufficiently generic that extending it to multiple reservoir systems is readily possible. The literature review has presented information on the simulation and operation of multiple reservoirs, both parallel, series and combination; this will replace the single reservoir simulation equations to accommodate multiple reservoir configuration. The inflow forecasting model using the ANN is also amenable to adaptation for multiple sites configuration without much difficulty. As noted by Adeloye (2009), one of the advantages of ANN modelling is that it is unconstrained as to the number of output variables. Thus, a way to adapt the ANN for the multivariate forecasting of the inflows at a number of sites is to increase the number of output variables to the number of reservoir sites in the problem being solved.

6.2 Limitations of the study

(1) Data recorded came from different sources, so the period of historical data was different. The Royal Irrigation Department (RID) provided the historical water demand of 384 months (April1980-Mach2012) and monthly rainfall data at Nong wai of 372 months (April 1981-March 2012). The reservoir monthly inflow data of 504 months (April1970-March2012) and the monthly rainfall data at the Ubonratana of 60 months (April2008-March2012) were provided by EGAT, the dam's operators. Therefore, this study used the data recorded of 360 months (April 1982-March 2012), except for the calculation of the net evaluation for the Ubonratana reservoir used 60 months of the monthly rainfall data recorded at Ubonratana. The monthly rainfall data at the Ubonratana were recorded over a short period and some of them were missing, so they are not suitable to be used for inflow forecasting. Therefore, the recorded rainfall data at Nong wai, located downstream of the reservoir, was used for inflow forecasting. However, longer historical data record of inflow at Ubonratana reservoir or upstream reservoir might provide more accuracy of inflow forecast.

(2) Mitigation of flood damages is of one the highest priorities for water resources management in the Chi River basin. The basin is protected from flooding through the operation of the Ubonratana reservoir using a flood control rule curve. For such a multi-purpose system serving flood protection and various water demand needs, it is important that the reservoir is effectively operated to ensure that the overall performance of the system is enhanced. Because of time limitations, however, the thesis only focused on optimising against the impact of droughts and formal optimisation in relation to its other functions, i.e. flood protection and hydro-power generation, were not included in the objective function. Extension of the study to include these in a multi-objective optimisation framework is possible and has indeed been recommended as possible future studies (see section 7.2). Nevertheless, it is important to stress that the current rule curves do support both purposes through the flood control rule curve and the prescribed minimum water level for hydropower generation.. It is believed that this should suffice until a more complete optimisation of the multi-purpose, multi-objective problem is done.

In-stream water requirements for sustaining the health of the river system have been based on a constant amount whose basis was not made known by EGAT. The fact that this demand has remained constant irrespective of the season is also questionable. Modern approaches to addressing environmental flow requirements would require rigorous analysis of the ecosystem services within the basin and how to sustain these services in the face of varying hydrologic and hydraulic situations in the basin. Consideration of these issues was not attempted in the study because of lack of time but it is important that EGAT and other stakeholders in the Chi River Basin are aware of its importance so that they can develop more robust estimates of environmental flows that address ecosystems services enhancement and sustainability.

(3) The allocation of water among the various use sectors- municipal, instream and irrigation- has followed the existing practice and stakeholders' preference at Ubonratana reservoir, which is a winner-takes-all situation. While this may have been valid for the case study, a common approach and one that can be deemed fairer is to allocate the scarce water resources based on a weighting system so that each user sector gets an allocation irrespective of the available water quantity. The challenge with this approach, however, is how to arrive at the appropriate weights to use. Chiamsathit et al. (2014) and Sandoval-Solis et al. (2011) suggested weights calculated on the basis of the proportion of total systems demand required by each sector. Alternatively, the weights could also be specified as decision variables and determined as part of the optimisation problem. Whatever approach is adopted, however, incorporating a weighted system of water allocation into the optimisation is relatively straightforward and would be a worthwhile and logical extension of the current study.

(4) Climate change impacts on the overall water cycle (evaporation and precipitation) and affects availability and demand of water resources. For example, increasing the rainfall will cause the streamflow (and hence reservoir inflow) to increase while decreasing it will result in the opposite effect (Adeloye et al., 2016). Changes in available water in storage will depend on changes in the volume, variability, and seasonality of runoff. In addition, climate change will probably alter the desired uses of water (target demands) as well as actual uses (demands in each sector that are actually met). For example, higher temperatures and increased variability of precipitation would, in general, lead to an increased irrigation water demand. The study of inflow forecasting has ignored the possible impact of predicted climate change on both the hydrology and demand. Climate change affects temperature, rainfall, evaporation and hence inflow of the reservoir as well as water demand for irrigation and other purposes. The effect of

such a change is to invalidate the assumptions of historical data which were used in the predicted inflow.

(5) Sectoral water demands can be expected to change over time in response to changes in population, settlement patterns, wealth, industrial activity, and technology. For example, rapid urbanization can lead to substantial localised growth in water demand, often making it difficult to meet goals for the provision of a safe, affordable, domestic water supply, particularly in arid regions (Faruqui, 2001). The study has ignored the possible impact of possible water demand increases on the results. The water demand affects water supply management. The future water demand could change the reservoir operation policy optimised with historical demand data.

Chapter 7 Conclusions and Recommendations for Future Research

7.1 Conclusions

In concluding this thesis, it will be pertinent to first review the aim and objectives of the study as set out in Chapter 1, to see the extent to which they have been achieved. The objectives were to:

(1) Review exhaustively the literature on reservoir planning and operation studies to identify good practices and knowledge gaps that can inform the development of the research methodology.

(2) Present the development of the new dynamic GA (DGA) optimisation and discuss its main features that distinguishes it from the standard GA (SGA).

(3) Apply both SGA and DGA to the optimisation of hedging-integrated rule curves for the operation of the Ubonratana multi-purpose reservoir in Thailand.

(4) Develop artificial neural networks (ANN) models for monthly inflow forecasting at Ubontarana.

(5) Carry out intensive simulation of the Ubonratana reservoir to assess the performance impacts, of any, brought about by water hedging and various assumed inflow knowledge situations including forecasting.

The first objective was covered by Chapter 2. The second objectives were achieved in 3.3 (Chapter 3). The third, fourth and fifth objectives were demonstrated by sections 5.3, 5.4 and 5.5 (Chapter 5). It is therefore clear that all of the objectives have been achieved Based on the entire study, the certain conclusions have emanated. These conclusions are set out below.

7.1.1 Reservoir operation is concerned with water allocation to maximise their efficiency and minimise their environmental damage. In general, simulation models can be used for developing operating policies; however, the process involves the repeated implementation of simulation models through the trial and error process (Kangrang and Hormwichian, 2008). Because the number of feasible solutions in optimising reservoir rule curves is quite large, the trial and error process in simulation is very time consuming and cannot guarantee the optimal solution. The genetic algorithm (GA) optimisation for the reservoir operation has been widely used and accepted as a robust method to search for the optimal solution to complex problems (Reddy and Kumar, 2006; Azamathulla et al., 2008). This study applied the GA optimisation for the operating rule curves of the Ubonratana reservoir in order to develop the existing operating policy. The results of this study demonstrated that the performance of the rule curves obtained by using GA optimisation is far superior to the rule curves obtained by using trial and error method proposed by Chiamsathit et al. (2014). Because GA optimisation uses a random search from a population of points, it has a greater possibility of arriving at the global optimum. The approach also has advantages over non-linear programming (NLP), because it produced fitter solutions (i.e. new generation) using reproduction, thereby reducing the tendency to become entrapped in local minima and avoiding a dependency on an assumed starting model.

7.1.2 The main challenge in standard GA optimisation is establishing the optimum boundary of the feasible region to search for the optimal solution. Too wide a boundary will increase the computational time and lead the solution trapping in local optima while too narrow a boundary may lead to the solution missing the global optimum (Purohit et al., 2013; Roeva et al., 2013). To solve this problem, a new development of the GA, known as the dynamic GA (DGA), was developed in this study in order to improve the SGA performance in finding the optimal solution. The concept of DGA is automatic modifying the constraint boundary by using the group of the best solution performance to update the new limit boundary to find the better search space for the global optimum. Consequently, DGA is insensitive to the initial constraint boundary. DGA is more efficient and more rapid than the standard GA (SGA) in arriving at an optimal solution, as shown by the benchmarking exercise using Shaffer'F7 objective function, the new dynamic GA (DGA) has much higher percentage of finding the global optimum. Since the best fitness value obtained by DGA optimisation developed in this work appears to be unaffected by establishing the initial boundary, the new algorithm could be applied to solving any optimisation problem, irrespective of the knowledge on initial search space boundary. This is a major advantage since the establishing optimal search space is a challenge in real world optimising problem, as stated earlier in the literature.

7.1.3 The comparative study using NLP, SGA and DGA was demonstrated by optimising a single-year rule curves policy in the worst inflow situations i.e. the year with the lowest mean inflow (1993) and the year with highest inflow variability as characterised by the coefficient of variation (CV) of annual inflow (2002). This is because in the longer period and more complex problems, NLP could not find the feasible solution for this study. This limitation has been reviewed in the literature whereby search methods of NLP sometimes become trapped in local optima (McMahon and Adeloye, 2005; Li et al., 1998; Hossain and El-Shafie, 2013). The minimisation of the sum squares of the period shortages is the objective function. The purpose of the optimisation is to reduce large, single period shortage. The results were compared to SGA and DGA. The lowest mean of inflow in 1993, the reservoir performance of the optimised policy using SGA and DGA were better than NLP curves. However, NLP optimisation works well as GA in a simple problem, as using NLP and GA does not affect the simulation results of the optimised rule curves in the inflow situation of 2002.

7.1.4 Rule curves policy defines upper and lower rule curves, to guide the reservoir release to meet water requirements. Therefore, in this study the genetic algorithm (GA) and the dynamic GA (DGA) were used for optimising the reservoir rule curves using the minimisation of the sum squares of the period shortages (SS) for the objective function. The purpose of the optimisation is to reduce large, single period shortage (vulnerability) in the existing policies. A reduction in the number and amount of unmet demand of the optimised policy clearly demonstrated the development of the existing policies by using GA optimisation. DGA provided better outcome than SGA. A further attribute of the DGA is its speed at arriving at the global optimum. In particular, the evaluated sustainability indices showed that the DGA was better than the SGA, for the individual water supply categories as well as their aggregation. The concept of rule curves policy is that as long as the available water at the start of a period is within the space bounded by the upper and lower curves, an attempt is made to meet the full demand during that period. Therefore, during low flow situation the release is cutback to restore the reservoir level to lower rule curve. The basic optimised rule curves reduced the total amount of shortage, R_t and R_v, as shown in this study. However, they could not temper the vulnerability. This is because this approach saves no water for impending droughts and the consequence is that the resulting shortage during such droughts can be very large.

7.1.5 Water rationing during normal operational periods i.e. rather than supplying the full demand, the release is curtailed by moderate amounts for impending droughts and the saved water can be used to reduce the impact of water shortages (Chiamsathit et al., 2014; Adeloye et al., 2016). The rationing of hedging is to reduce large shortages by sacrificing more smaller shortages; it is better to have many small water shortages to which water users can readily adapt than fewer large, crippling shortages (Tu et al., 2003; 2008: Eum et al., 2011). In general, vulnerability over 25% is not recommended because it can cause severe stress for users (Fiering, 1982). Therefore, the optimised hedging policies integrated rule curves were developed in this study to overcome this problem. The two types of objective functions (i.e. SS and MSI objective functions) used in this study attempted to minimise the volume of single-period shortage by using the square deficit; thus the individual deficit magnitudes are squared in order to penalise the large deficit and convert them into a smaller deficit. Therefore, more frequent small shortages were generated leading to reducing the vulnerability. However, the consequence of implementing the hedging is the resulting longer period of deficit leading to decreasing the resilience. The number of water shortages increased with the optimised hedging rules, causing the time-based reliability to worsen significantly. This should not be of concern since, although the number of shortages increased, the associated shortage quantities on most of these additional occasions were small, leaving the volumetric reliability largely unchanged.

7.1.6 The hedging policy is applied whenever the reservoir storage falls below a critical level for each month of the year that lies between the upper and lower curves. This is to be expected given that, in the optimisation solution, the upper boundary of the conservation upper rule curve was set to be below the flood rule curve. Thus the performance of the reservoir with regard to flood protection is not expected to be affected by the newly derived hedging-integrated rule curves. The decision variables, i.e. the set of monthly storages defining the critical rule curve that triggers rationing and the rationing ratio, were optimized by genetic algorithm (GA). Both single stage (i.e. with one critical rule curve and one rationing ratio) and two-stages (with two critical rule curves and ratios) of the hedging policy were considered in the optimization. Subsequent reservoir simulations to test the effectiveness of the hedging rules show that significant reduction in the number of large single-period water shortages can be achieved by rationing, resulting in manageable vulnerability for the Ubonratana. This situation highlights the benefit of water saving during normal reservoir operation because it can bring about a significant reduction in the impact of large single-period shortage. In terms of the vulnerability, the two-stage hedging outperformed both the single-stage and no-hedging policies. Because the two-stage hedging contains two critical curves of rationing the first curve of hedging starting early with small rationing ratio and the second curve staring later with a higher rationing ratio, there was more water saving during normal operation.

7.1.7 The number of large single-period water shortages is significantly reduced by the optimised hedging using the objective function of modified shortage index (MSI). The results of two-stage hedging demonstrated that the vulnerability of all sectors was reduced lower than 25% of water demand, as recommend by Fiering (1982). Because this objective defined the rationing ratio for each demand sectors, the value of the rationing ratio reflected the priority, for example, the lowest priority has highest rationing ratio. Consequently, water shortage was proportionally shared among all demand sectors, rather than to just the low priority (irrigation sector) in the hedging stage. This has eliminated all occurrences of fully-unmet demands.

7.1.8 Reservoir operation concerns taking decision on water release from a reservoir based on the water available i.e. the sum of the starting storage level and the expected inflow during the period. Therefore, effective reservoir operation relies on reliable forecast of inflow into the reservoir. ANNs have the ability to forecast non-stationary time series data (Edossa and Babel, 2012) and Mohammadi et al., 2005). The MLP-ANN developed in this study was satisfactorily used for one-month-ahead inflow forecasts. Several models were tested for several numbers of input variables and hidden neurons to find the best architecture network for forecasting. To access how well the forecast inflows have performed in the operation of the reservoir, simulations were carried out guided by the rule curves and hedging policies. The reservoir operation with the forecast inflows situation produced the best performance while the situation of unknown inflow was the worst performing, because for the latter release decision was conditioned on the starting reservoir storage. The use of historic average inflow situation provided higher occurrences of storage volume below the lower rule curve than the forecast inflow situation because in some months inflows were higher than the forecast inflows and actual inflows, leads to large water is released in those months. All this clearly demonstrates that the forecast inflows with good accuracy are essential for effective reservoir operation.

7.1.9 Although the case study was a single reservoir system, the developed methodology is sufficiently generic that extending it to multiple reservoir systems is readily possible. The literature review has presented information on the simulation and operation of multiple reservoirs, both parallel, series and combination; this will replace the single reservoir simulation equations to accommodate multiple reservoir configuration. The inflow forecasting model using the ANN is also amenable to adaptation for multiple sites configuration without much difficulty. As noted by Adeloye (2009), one of the advantages of ANN modelling is that it is unconstrained as to the number of output variables. Thus, a way to adapt the ANN for the multivariate forecasting of the inflows at a number of sites is to increase the number of output variables to the number of reservoir sites in the problem being solved.

7.1.10 Reservoirs are a major component of water supply systems but changes orchestrated by climate, land and other environmental changes are affecting the ability of reservoirs to effectively perform their function both now and in the future. The obvious solution to the problem is the development of new sources but the scope for doing so is rapidly disappearing. The outcome of this study, in which simple changes to operational practices through water hedging have helped to temper the impacts of water shortage, is something that reservoir operators everywhere can adopt. If properly designed, the approach will not only improve water security but will also go a long way in reducing flood risk.

7.2 Recommendations for Future Research

7.2.1 While this thesis set out the flood control rule curve as the maximum limit for the optimising upper rule curve and used the minimum of hydropower generation level for the optimising lower rule curve, future research should incorporate other objective function such as minimising flood impact and maximising hydropower generation for the optimisation of the reservoir operating policy. In this case, the problem of multi-objective, multi-purpose reservoir management should be considered for defining optimal reservoir operations.

7.2.2 As stated earlier, the optimal hedging policy benefits water saving during normal reservoir operation because it can bring about a significant reduction in the impact of a large single period of water shortage. In terms of the vulnerability, the two-stage hedging outperformed both the single-stage and no-hedging policies. Additionally, in term of the volume-based reliability index for the single-stage and two-stage hedging was not significantly affected. This might be an indication that further refinements of the hedging policy to include for example three stages or four stages might be warranted and this aspect is being taken up as the next stage of the future study.

7.2.3 The study of inflow forecasting has ignored the possible impact of predicted climate change on both the hydrology and demand. Future research would be necessary to investigate their impact on the inflow forecasting.

7.2.4 The possible impact of possible water demand increases on the results should be considered because the water demand affects water supply management. The future water demand could change the reservoir operation policy optimised with historical demand data. Future research would be necessary to investigate such issues on the optimised reservoir policy.

7.2.5 The treatment of environmental flows in the study has been rudimentary, largely based on the practice at reservoir. However, recent concerns about ecosystems services and their sustainability mean that such an approach may not be justified and would need to be updated.

7.2.6 In this study, the objective function in the optimisation prioritises demand allocation in the following order: public demand, downstream, and irrigation, respectively (same order from low to high volume of demand), where there is no need to provide weights for the objective function. Therefore, the objective function used in this study results in a fixed allocation relied on the priority demand of the Ubonratana reservoir. Alternatively, the weights would be specified as decision variables and determined as part of the optimisation problem for the future research.

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